DESIGN AND ANALYSIS OF BRAIN EMOTIONAL LEARNING BASED INTELLIGENT CONTROLLER (BELBIC) FOR TEMPERATURE CONTROL

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By

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Submitted to the Electrical & Electronics Engineering Programme
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CERTIFICATION OF APPROVAL

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Approved:

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Project Supervisor

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TRONOH, PERAK

June 2010

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Siti Rasyidah binti Syed Rabi'i

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May Allah S.W.T. bless all of you.

ABSTRACT

This report presents the project undertaken to design and analyze the performance of temperature control using brain emotional learning control approach. In recent years, theory and applications of intelligent control systems have been a focus in control engineering. Among intelligent control approaches are Artificial Neural Network, Fuzzy Control and Genetic Algorithm. Recently, a computational model based on the model of brain limbic system has been developed. The limbic system, which consists of several components that carry out different tasks, is responsible for emotional processes. The intelligent controller, called brain emotional learning based intelligent controller (BELBIC), has a simpler computational algorithm as compared to other artificial intelligent control approaches. BELBIC is claimed to have output of fast response and robust performance. This study mainly deals with algorithm and computational model for controlling nonlinear temperature process using BELBIC. In this project, BELBIC and PID control approaches are used with temperature process transfer function. Methodology towards accomplishing the project includes the theoretical and technical research, designing and modeling BELBIC and PID controller using SIMULINK, tuning and simulating the controllers. The findings demonstrate the simulation results which reveal the performance of both controllers and the effectiveness of brain emotional learning approach in control engineering.

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

In recent years, biologically motivated intelligent algorithm has been widely applied in control engineering for solving different types of problems. The fundamental property that distinguishes an intelligent system from a traditional system is its capability to learn and adapt with the input from the environment. The learning process can occur at different levels of complexity, but a common property is the adaptation of the system parameters to respond better with the changing environment. Researchers nowadays appreciate the limitations of traditional approaches when dealing with uncertainties and complexities associated with real world situations and the possibilities for overcoming these problems inherent in intelligent approaches [1].

Till late, emotions were considered a negative trait by neurophysiologists and were considered a weakness of the human being. Emotional thought is considered to be unintentional and there exists little conscious control over such thought. Nevertheless, these unintentional emotions can easily and frequently change conscious thought [2]. However, studies have been carried out which prove that emotional process actually helps in learning. For example, in [3], one single occurrence of an emotionally charged-up situation remains in one's memory for years to come, whereas the memory of some tasks that one performs daily would not be equally vivid and easily recalled.

Emotional learning which happens in limbic system of the brain is one of biologically motivated intelligent algorithm. In late 1990's, with inspired by emotional learning process in mammalians brain, an intelligent controller called brain emotional learning based intelligent controller (BELBIC) has been developed by J. Moren and C. Balkenius [4].

1.2 Problem Statement

The most basic controller used in process plants nowadays is the Proportional Integral Derivative (PID) controller. PID controller may give poor performance as the loop gain needs to be reduced to ensure the process does not overshoot or oscillate. Artificial intelligent controller approaches such as Artificial Neural Network, Fuzzy-logic Control and Genetic Algorithm have shown successful results in regulating the process behavior; however, these control approaches require complex computation. Brain Emotional Learning Based Intelligent Controller (BELBIC) is intelligent controller that has simpler computational method; which will be applied in this project.

1.3 Objective and Scope of Study

The objective of this project is to design BELBIC and to determine the performance and applicability of BELBIC for temperature control. The study mainly deals with various aspects of modeling the emotional learning process that happens in the brain limbic system and applying it for temperature control. The simulation result of BELBIC is to be compared with that of PID controller and the performance of both controllers are analyzed.

The scopes of this study are as the following:

a. Designing BELBIC to control nonlinear temperature process in SIMULINK.
b. Designing PID controller for the same nonlinear temperature process in SIMULINK.
c. Developing analytical studies of emotional learning control and PID control to determine the control performance of the controllers.
d. To compare the performance of BELBIC with that of PID controller.

CHAPTER 2

LITERATURE REVIEW

2.1 Brain Emotional Learning Based Intelligent Controller (BELBIC)

2.1.1 Emotional Process in Limbic System

Human and other mammals are known to have emotional behaviors. This decision making process in nervous system of human and other animals, help them to survive in dangerous conditions. Cognitive studies have been undertaken for modeling and describing emotion and memory in animals. Also based on these studies, emotion can be considered as a tacit expert system [5].

The limbic system is a set of brain structures in mammalian which is responsible for emotional responses, emotional controls, mood, motivation, pain and pleasure sense and hormonal secretions functions. This system is also responsible for some aspects of personal identity and for important functions related to memory.

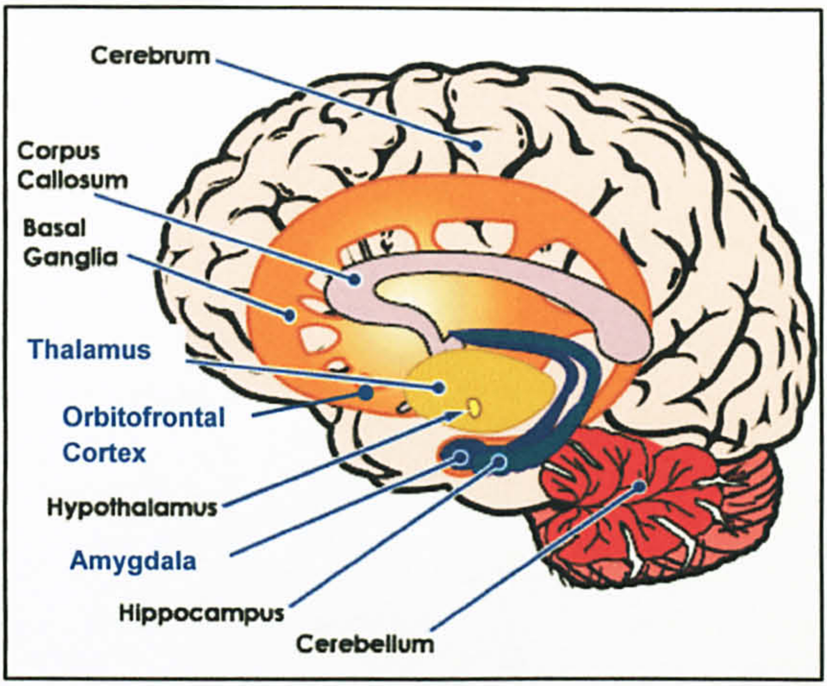

Figure 1: Architecture of limbic system

The primary structure of limbic system is shown in Figure 1. The amygdala, the orbitofrontal cortex, the thalamus and the sensory cortex are the main components that involve in emotional processing. From the mentioned components, the first two play a key role in the processing of emotions while the other two largely function as preprocessors of sensory input [6].

The amygdala is a small structure in the medial temporal lobe that is thought to be responsible for the emotional evaluations of stimuli. This evaluation is in turn used as a basis for emotional states, for emotional reactions and is used to signal attention and laying down long-term memories [7]. The amygdala reacts to a number of innate stimuli that have a priori emotional charge, such as hunger, pain, certain smells and other stimuli. Whenever such a stimulus is encountered, the amygdala will elicit a set of responses that are used in motor learning and in the attention system. A particular set of stimuli is received directly from the thalamus, rather than from the stimuli cortices which works as an early, fast sensory classification system [7].

The orbitofrontal cortex is a prefrontal cortex region in the frontal lobes in the brain which involved in the cognitive processing of decision making. Decision making is not mediated by the orbitofrontal cortex alone, but arises from large-scale systems that include other cortical and subcorticol components, including the amygdala, the somatosensory cortices and the peripheral nervous system [8]. In human brain, the orbitofrontal cortex is involved in sensory integration; in representing the affective value of reinforcers or reward, and in decision-making and expectation [9]. In particular, the human orbitofrontal cortex is thought to regulate planning behavior associated with sensitivity to reward and punishment [10]. The orbitofrontal cortex is known to inhibit areas it is connected to and there are also connections both from and to the amygdala. Whereas the amygdala learns appropriate associations between neutral and emotionally charged stimuli, the orbitofrontal cortex inhibits the expression of these associations as needed depending on context and other factors [7].

The thalamus is situated between the cerebral cortex and midbrain, both in terms of connection and neurological connections. Its function includes relaying sensation, special sense and motor signals to the cerebral cortex, along with the regulation of consciousness, sleep and alertness. In particular, the task of the thalamus is to provide a non-optimal but fast response to stimuli. This capability is often simulated by passing the maximum signals, overall sensory signals, to the amygdala. The main task of the sensory cortex in biological systems is to appropriately distribute the incoming sensory signals through the amygdala and the orbitofrontal cortex [5].

2.1.2 BELBIC Structure

BELBIC is divided into two main parts: roughly corresponding to the amygdala and orbitofrontal cortex, respectively. In this section, a short description about every part of BELBIC is explained. The structure of BELBIC is shown in Figure 2, while the simplified BELBIC structure is shown in Figure 3.

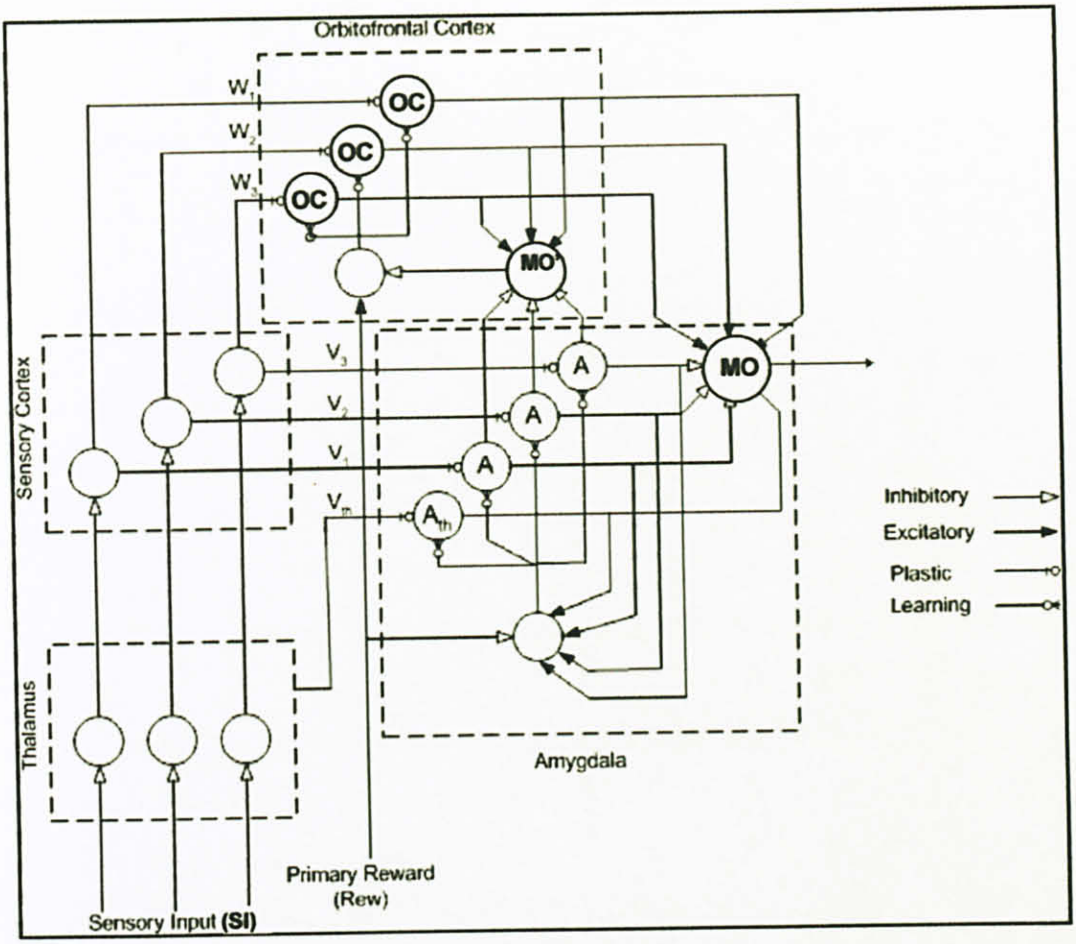

Figure 2: BELBIC structure

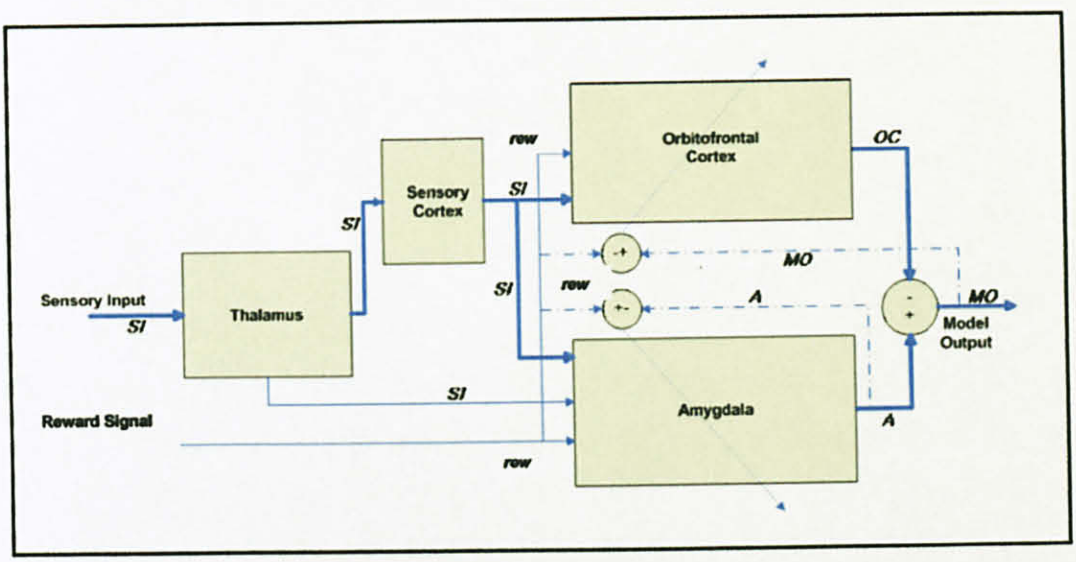

Figure 3: Block diagram of simplified BELBIC structure

Thalamus is a simple model of real thalamus in mammalians' brain. Some simple pre-processing on sensory input signals such as noise reduction or filtering can be done in this part. The thalamus prepares the sensory cortex needed input which to be subdivided and distinguished [5].

At first, sensory input signals are going into thalamus for pre-processing on them. Then amygdala and sensory cortex will receive their processed form and their outputs will be computed by amygdala and orbitofrontal cortex based on the emotional signal received from environment. Orbitofrontal cortex is supposed to inhibit inappropriate responses from amygdala based on the context given by the hippocampus. Final output is subtraction of amygdala and orbitofrontal cortex [7]. One of amygdala's inputs is called thalamic connection and calculated as the maximum overall sensory input *SI*. The thalamic input is different from other amygdala's inputs as it is not projected into the orbitofrontal part and cannot be inhibited by itself.

2.1.3 BELBIC Algorithm

In this section, the learning algorithm and functions of BELBIC parts as shown in Figure 2 is explained based on [5].

The algorithm for thalamic input is as follows:

$$Ath = \max(SIi) \tag{1}$$

where *A* is amygdala and *SI* is sensory input. Every input of *A* node is multiplied by a plastic weight *Vi* to give the output of the node. For *OC* nodes, there is connections weight *Wi* applied to the input signal to create the output. The connection weights *Vi* are adjusted proportionally to the difference between the emotional stress and the activation of the *A* node. A constant parameter α or learning rate of amygdala is used to adjust the learning rate. With reference to Equation (2), amygdala learning rule is presented.

$$\Delta Ga_i = \alpha(SI_i \max(0, rew - \textstyle\sum A_j)) \qquad (2)$$

where α is learning rate of amygdala, *rew* is reward signal and *Ga* is plastic weight or simply gain of each *Ai* (including *Ath*). This is an example of a simple associative learning system. The genuine difference between this system and similar associative learning systems is that this weight-adjusting rule is monotonic, which the weights *Ga* cannot decrease. The reason behind this design is that once an emotional reaction has been learned, it should be permanent. It is the task of the orbitofrontal cortex part to inhibit this reaction when it is inappropriate [5].

Similarly, the learning rule for *OC* nodes is calculated as the difference between the previous output *OC* and the reward signal *rew*.

$$\Delta Goc_i = \beta(SI_i \textstyle\sum(OC_j - rew)) \qquad (3)$$

where *Goc* is the gain in orbitofrontal cortex connection and β is learning rate of orbitofrontal cortex which is a constant value. The *OC* nodes compare the expected and received reward signals; therefore, inhibiting the output of the model should be a mismatch. The orbitofrontal cortex learning rule is very similar to the amygdala rule. The only difference is that the orbitofrontal cortex connection weight can increase or decrease as needed to track the required inhibition. The *A* nodes produce the outputs proportionally to the contribution in projecting the reward signal, while the *OC* nodes inhibit the output of *MO* when necessary.

There is one output node *MO* which is in common for all outputs of the model. The amygdala acts as an actuator and orbitofrontal cortex acts as a preventer. The *MO* node sums the outputs from *A* nodes, then subtracts the outputs from *OC* nodes. The result is the output of the model. The *MO'* node is the summation of the outputs from *A* nodes except for *Ath* and subtraction from inhibitory outputs from *OC* nodes.

$$MO = \sum Ai - \sum OCi \qquad \text{(including } Ath\text{)} \tag{4}$$

$$MO' = \sum Ai - \sum OCi \qquad \text{(not including } Ath\text{)} \tag{5}$$

Finally, the node values are calculated as follows:

$$Ai = SIiGai \tag{6}$$

$$OCi = SIiGoci \tag{7}$$

Since amygdala is not capable to unlearn any emotional response that it ever learned, inhabitation of any inappropriate response is the task of orbitofrontal cortex. In simpler words, the system works at two stages: at first stage the amygdala part learns to project and react to a given reward. It can never unlearn a connection; once learned, it is permanent which makes the system to be able to retain emotional connections as long as necessary. At second stage, the orbitofrontal cortex system tracks mismatches between the amygdala system's projections and the actual received input and learns to restrain the system output from being proportional to the mismatch.

2.1.4 Control System Structure

The emotional learning mechanism in mammalians is an open-loop learning system which the living creature receives stimuli from the environment and reacts respectively. The effectiveness of this reaction is evaluated based on reward signals which help the creatures to reproduce better responses. A closed-loop scheme must be introduced in order to use this algorithm for control applications and decision making. A schematic diagram of closed-loop decision making mechanism is shown in Figure 4 [11].

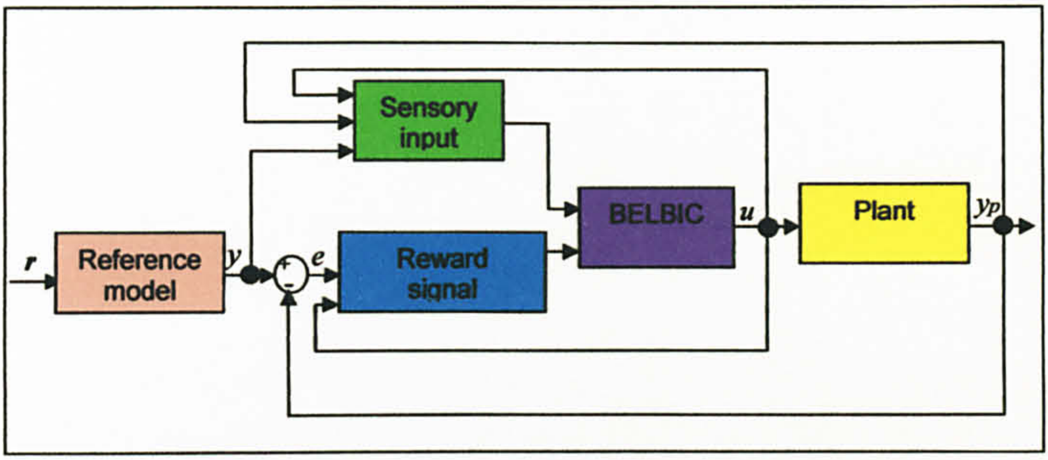

Figure 4: Control system configuration using BELBIC

Inputs to emotional learning mechanism are a set of sensory input signals and a reward signal. These signals can be randomly selected by the designer of the control algorithm. Reward signal, like its name, the controller try to increase this reward. It is recommended that the reward signal *rew* is a function of other signals which can be supposed as a cost function rationale, specifically award and punishment, as presented in (8) [11].

$$rew = J(SIi, e, yp) \tag{8}$$

where *SI* is sensory input signals, *yp* is the plant output and *e* is the error signal. Similarly the sensory inputs must be a function of plant outputs and controller outputs, as presented in (9) [11].

$$SI = f(u, e, yp, yr) \tag{9}$$

where *u* is controller output, *e* is error signal, *yp* is plant output and *yr* is the reference signal. From (8) and (9), sensory input and reward signal can be randomly function of the reference output, *yr*, controller output, *u* and error signal, *e* [11].

2.1.5 Advantages of BELBIC

BELBIC is an artificial intelligent controller that uses simpler algorithm as compared to other artificial intelligent controller. The computation is simple and easy to develop. BELBIC has a robust capability in compensating for disturbance in the process variables due to its ability to predict for errors.

2.1.6 Applications of BELBIC

BELBIC application in various control process are proposed and adapted, with some of them are presented in [12, 13, 14, 15].

a. Control of Heating, Ventilating and Air Conditioning (HVAC)System

In [12], the paper applies a modified version of BELBIC for Heating, Ventilating and Air Conditioning (HVAC) control system whose multivariable, nonlinear and non-minimum phase nature makes the task difficult. The proposed biologically-motivated algorithm achieves robust and satisfactory performance even though there are more than one control inputs to the plant, which may be used to get the desired performance. The response time is also very fast despite the fact that the control strategy is based on satisfying decision making. The proposed strategy is very flexible and alternative performance specifications can easily be enforced via defining proper emotional cues.

b. Control of A 2-DOF Helicopter Model

In [13], the paper discusses controlling a nonlinear model of a helicopter using BELBIC. Feedback linearization method has been applied to the system, and the performance of two controllers has been compared as an intelligent and a classical control method. An input to state linearization method with some changes has been used to control the system.

c. Control of Washing Machine

In [14], it uses two techniques to control a washing machine. The first is by using a neurofuzzy locally linear model system for data driven modeling of the machine, and the second is by using a neural computing technique, based on a mathematical model of amygdala and the limbic system, for emotional control of the washing machine. This paper also discusses energy conservation of BELBIC as compared to Fuzzy controller.

d. Traffic Control of ATM Networks

In [15], an intelligent controller is applied to traffic control of ATM Networks. First, the dynamics of the network is modeled by a Locally Linear Neurofuzzy Models. Then, an intelligent controller based on brain emotional learning algorithm is applied to the identified model. Simulation results show that the proposed fuzzy traffic controller can outperform the traditional Usage Parameter Control (UPC) mechanisms. Simulation results showed that the proposed emotional based controller demonstrates much better selectivity and effectiveness than the other conventional UPC mechanisms.

2.2 PID Controller

2.2.1 PID Algorithm

A PID controller is a combination of three separate controllers *Proportional (P)*, *integral (I)* and the *Derivative (D)* controllers. The proportional term considers how far process variable (PV) is from set point (SP) at any instant in time. Its contribution to the controller output is based on the size of error. The influence of the proportional term grows or shrinks immediately and proportionately.

The integral term addresses how long and how far PV has been away from SP. The integral term is continually summing error. Thus, even a small error, if it persists, will have a sum total that grows over time and the influence of the integral term will similarly grow. The magnitude of the contribution of the integral term to the overall control action is determined by the integral gain, K_i.

A derivative describes how steep a curve is. More properly, a derivative describes the slope or the rate of change of a signal trace at a particular point in time. Accordingly, the derivative term in the PID equation considers how fast, or the rate at which, error (or PV) is changing at the current moment. The magnitude of the contribution of the derivative term to the overall control action is determined by the derivative gain, K_d.

PID controller works in a closed-loop system using the schematic shown in Figure 5. The variable (e) represents the tracking error, the difference between the desired input value (R) and the actual output (Y). This error signal (e) will be sent to the PID controller, and the controller computes both the derivative and the integral of this error signal. The signal (u) just past the controller is now equal to the proportional gain (Kp) times the magnitude of the error plus the integral gain (Ki) times the integral of the error plus the derivative gain (Kd) times the derivative of the error. The transfer function of the PID controller is as the following:

$$\mathrm{Kp} + \frac{\mathrm{Ki}}{\mathrm{s}} + \mathrm{Kds} = \frac{\mathrm{Kds} + \mathrm{Kps} + \mathrm{Ki}}{\mathrm{s}} \tag{10}$$

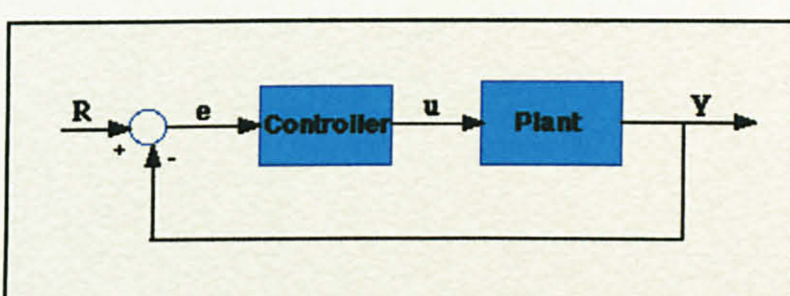

Figure 5: Closed loop system schematic

This signal (u) will be sent to the plant, and the new output (Y) will be obtained. This new output (Y) will be sent back to the sensor again to find the new error signal (e). The controller takes this new error signal and computes its derivative and integral again. This process goes on and on.

CHAPTER 3

METHODOLOGY

3.1 Procedure Identification

3.1.1 Project Flow

The project flow of designing BELBIC controller and PID controller for temperature process is simplified in Figure 6 below:

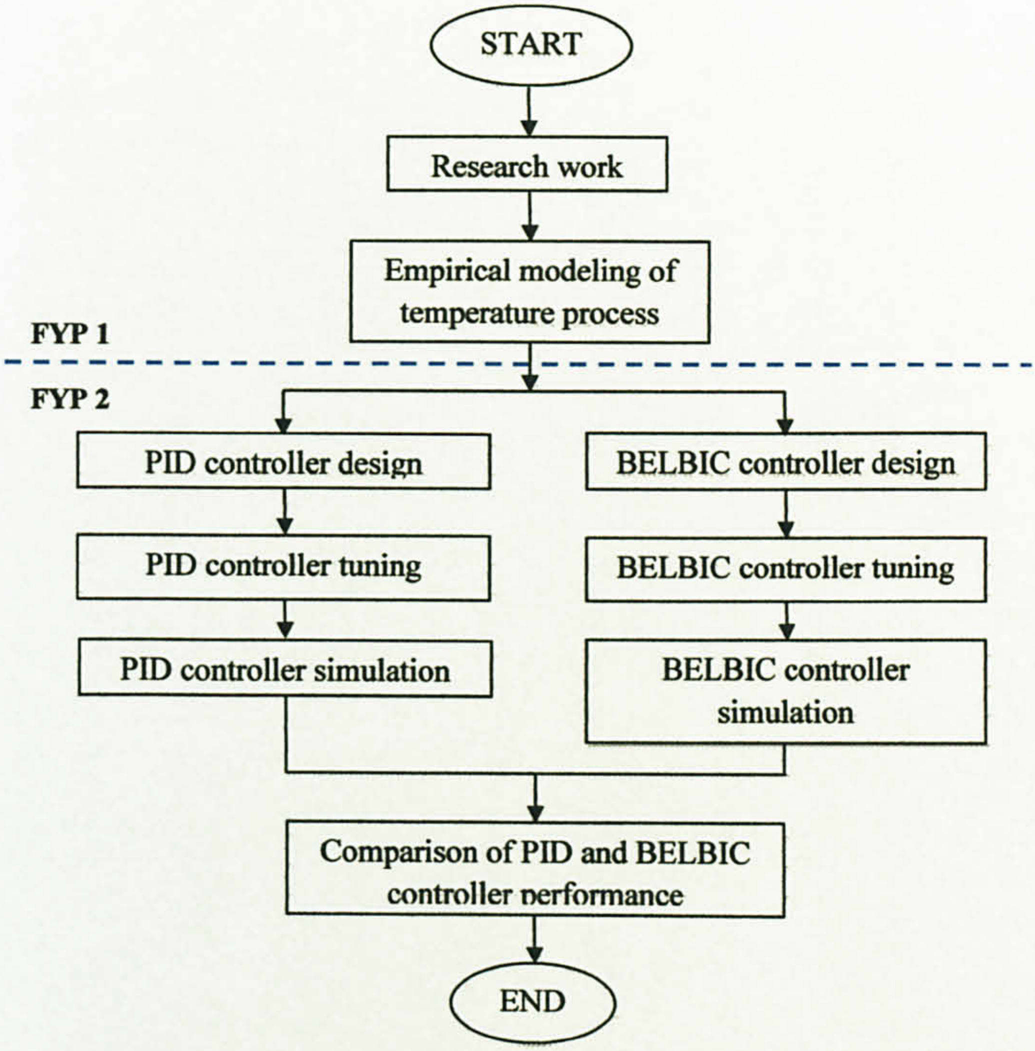

Figure 6: Project flow

3.1.2 Process Transfer Function

a. Control Loop

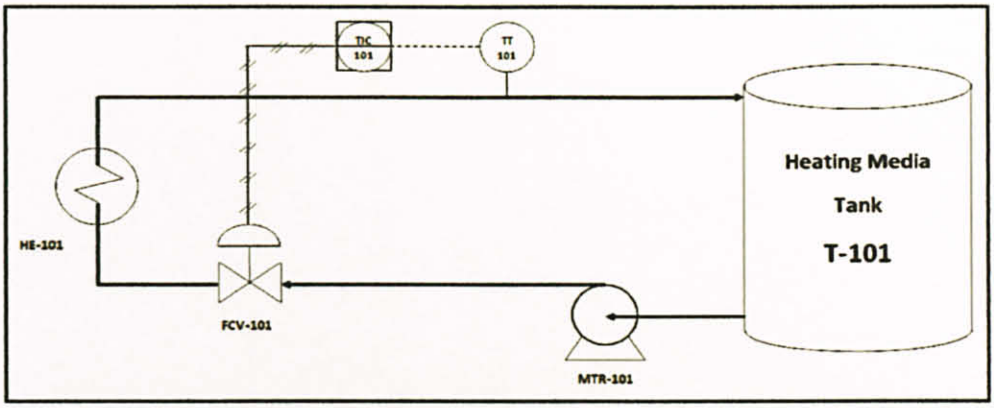

Figure 7: Temperature control loop P&ID

Figure 7 above shows the control loop Piping and Instrumentation Diagram (P&ID) for temperature control from the pilot plant at the Plant Process Control System Laboratory. This control loop is the subject of this project.

b. Empirical Modeling

Empirical modeling is the technique applied in this project to build a model that provides the dynamic relationship between selected input and output variables through experiment. In empirical modeling building, models are determined by making small changes in the input variable(s) about a nominal operating condition. The resulting dynamic response is used to determine the model [16]. Six-step procedures should be followed to ensure proper data is generated through careful experimental design and execution. The six-step procedure is shown in Figure 8. Empirical modeling method is used to get the transfer function in order to model the BELBIC and PID controllers.

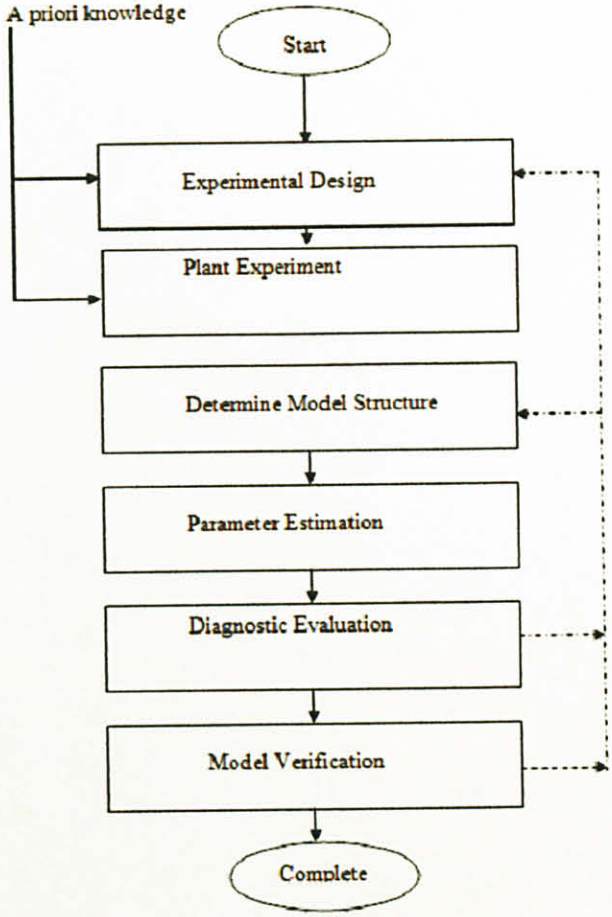

Figure 8: Empirical modeling procedures [16]

c. *Process Reaction Curve Method*

The process reaction curve is identified by doing an open loop step test of the process and identifying process model parameters. The process reaction curve method involves the following four steps:

i. Allow the process to reach steady state.
ii. Introduce a single step change in the input variable.
iii. Collect the input and output response data until the process gain reaches steady state.
iv. Perform the graphical process reaction curve calculation.

The model is based on the first order with dead time model. The model equation is shown as:

$$\frac{Y(s)}{X(s)} = \frac{K_{p}e^{-\theta s}}{\tau s+1} \qquad (11)$$

Where;

Kp= Process gain

τ= Time constant

θ= Dead time or time delay

Once the process reaction curve is obtained, there are two methods to calculate the process parameters; Method I and Method II. The elaborations on these methods are presented in Appendix A.

3.1.3 Feedback Control

In designing the model, a simple continuous feedback control is applied in the loop. The difference between the process variable value and the set point value or simply error is fed back to the controller to compensate for the error until the set point value is achieved. Feedback control is effective for all disturbances and can provide zero steady-state offset.

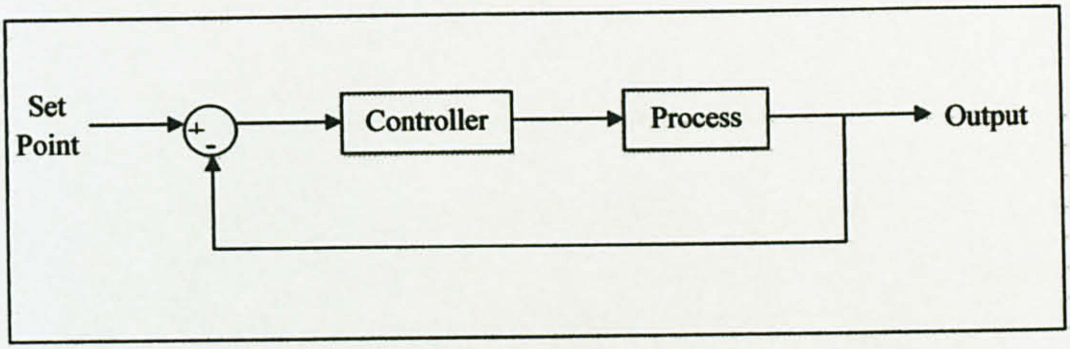

Figure 9: Feedback control loop

3.1.4 Anti-reset Windup

BELBIC algorithm applies much integration. Due to that, integral windup would be an issue. Modification is done in BELBIC design to achieve anti-reset windup by adding external feedback to the control algorithm.

3.2 Project Activities

3.2.1 Selection of Control Loop

The project activities including the following:

a. Performing empirical modeling on temperature control loop.
b. Calculating and get the transfer function of the process variable.

3.2.2 BELBIC Controller Design

The project activities including the following:

a. Designing BELBIC with plant model in SIMULINK.
b. Tuning BELBIC using trial and error method.
c. Simulating plant model with BELBIC.
d. Analyzing BELBIC performance.

3.2.3 PID Controller Design

The project activities including the following:

a. Designing PID controller with plant model in SIMULINK.
b. Tuning PID controller using Cohen-Coon and Ziegler-Nichols tuning correlations.
c. Simulating plant model with PID controller.
d. Analyzing PID controller performance.

3.2.4 Comparison of BELBIC and PID Controller Performance

The simulation results of both controllers are compared.

3.3 Tools and Equipments

a. Pilot Plant, Plant Process Control System Laboratory, Universiti Teknologi PETRONAS.
b. SIMULINK software.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Process Reaction Curve

The empirical modeling was performed over the pilot plant and process reaction curve was obtained. A step input of 25% was given to the system and the output change result in approximately 9.3°C of increment. The process parameters obtained are tabulated in Table 1.

Table 1: Process parameters from process reaction curve

Change in perturbation/MV, δ	25%
Change in output/PV, Δ	9.3 °C
Time at 28% of Δ ($t_{28\%}$)	1.47 min
Time at 63% of Δ ($t_{63\%}$)	9.03 min

The process parameters are calculated using Method II and the results are tabulated in Table 2:

Table 2: Process parameters

Process gain, Kp	0.372 °C/% open
Time constant, τ	11.34 min
Time delay, θ	2.33 min

The transfer function of the process is as follow:

$$G(s) = \frac{0.372\, e^{-2.33s}}{11.34s+1} \tag{12}$$

Ultimate sensitivity test is done to find the ultimate gain and ultimate period before the process becomes unstable. The results of the test are tabulated in Table 3.

Table 3: Results of ultimate sensitivity test

Ultimate gain, Ku	21.95
Ultimate period, Pu	8.98 s

4.2 BELBIC

4.2.1 BELBIC Design

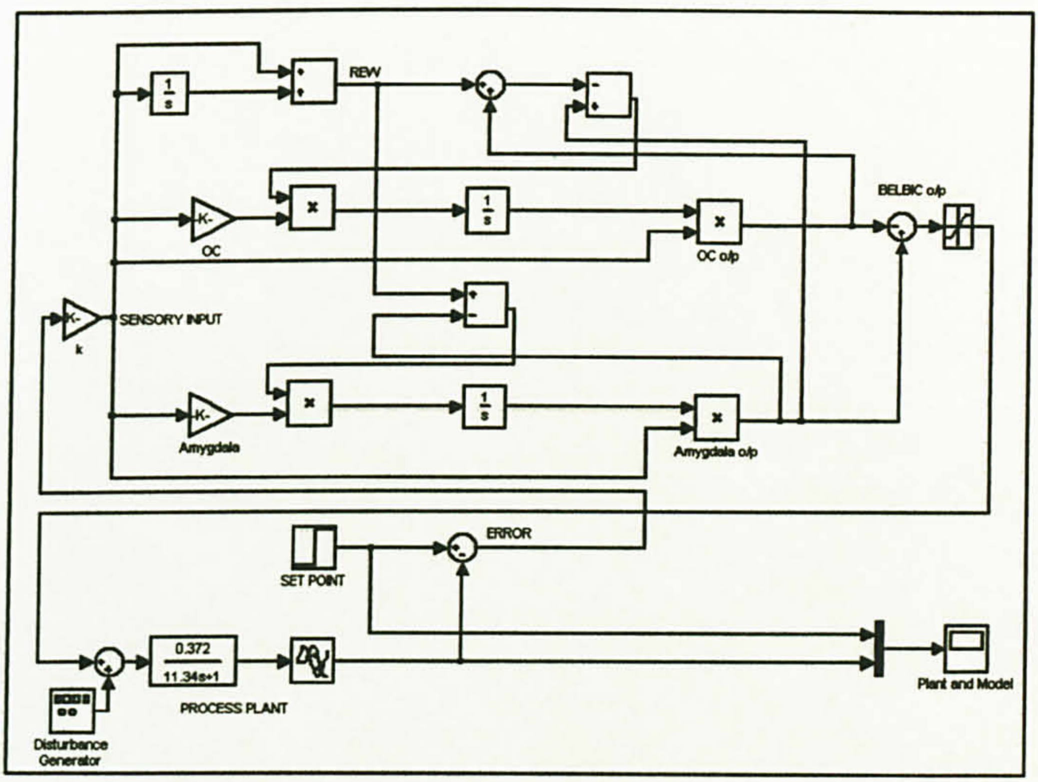

Figure 10: BELBIC schematic

BELBIC design schematic in SIMULINK is shown in Figure 10. A step input of value 10 is used as the set point. The sensory input (*SI*) and reward signal (*rew*) are as the following:

$$SI = Ke \tag{13}$$

$$rew = K\,(e + \int e\,dt) \tag{14}$$

For simplicity, the max operator in equations (2) – (7) is removed. The simplified set of equation used is as the following:

$$\frac{dGa}{dt} = \alpha.\ SI.\ (rew - A) \tag{15}$$

$$\frac{dGoc}{dt} = \beta.\ SI.\ (A - OC - rew) \tag{16}$$

$$MO = A - OC \tag{17}$$

$$A = Ga.SI \tag{18}$$

$$OC = Goc.SI \tag{19}$$

4.2.2 BELBIC Tuning Analysis

Figure 11 shows the open loop response of the process. A step input of value 10 is used as the set point and random disturbance of amplitude 1 is used for the disturbance.

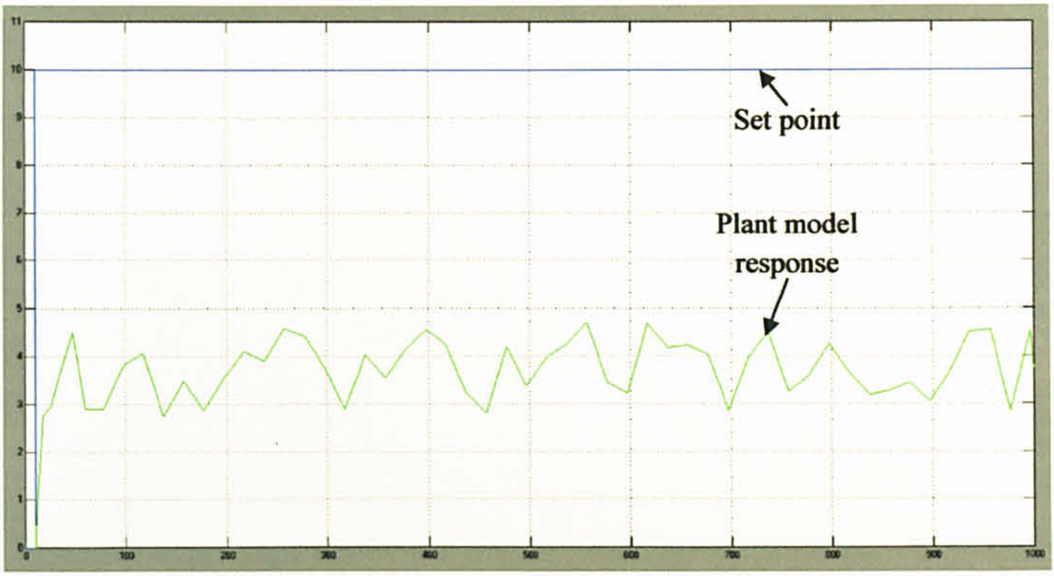

Figure 11: Process response of plant model with disturbance without controller (open loop response)

Since there is no specific method to tune BELBIC parameters, the controller is tuned using trial and error method. The trial is run from a value as small as zero until as large as 1000. For α and β tuning, a gain of K=0.2 is randomly chosen.

a. Effect of Learning Rate of Amygdala (α)

Figures 12 – 19 show the effect of learning rate of amydala for different values of α. Blue graph indicates set point and green graph indicates plant model response.

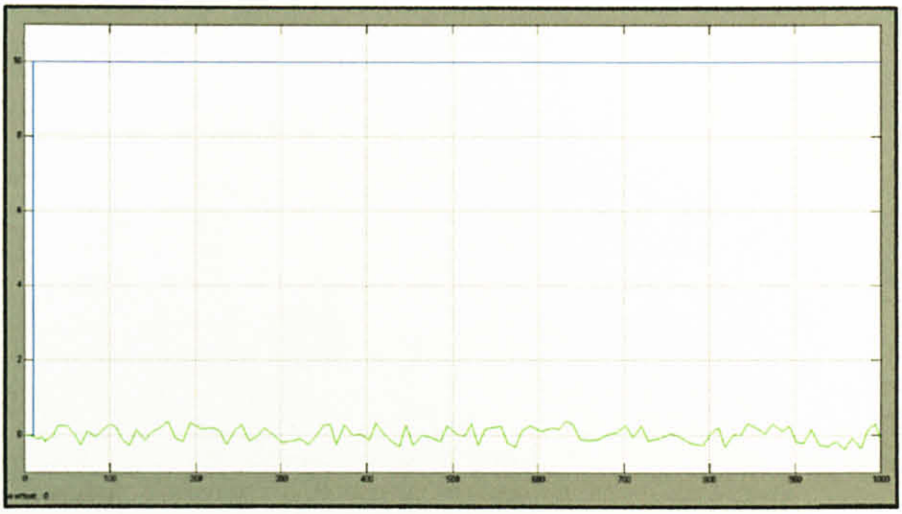

Figure 12: K=0.2, β=0, α=0

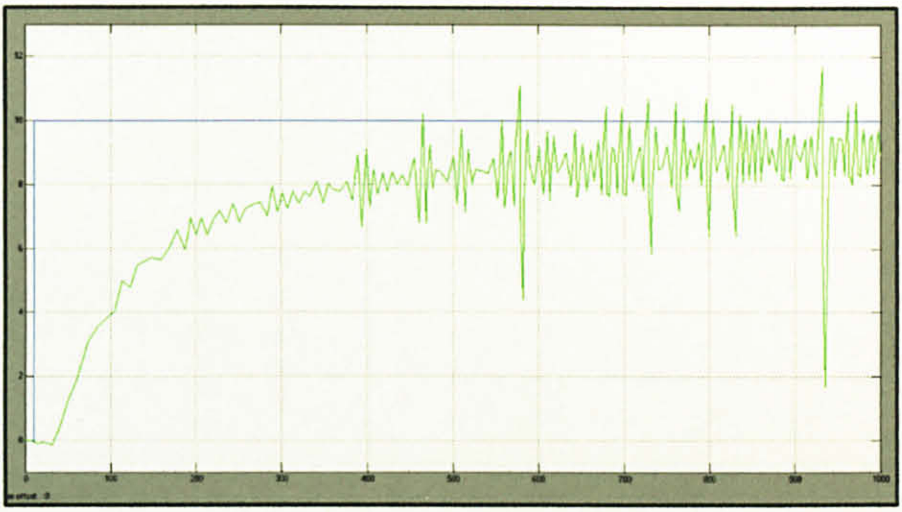

Figure 13: K=0.2, β=0, α=0.001

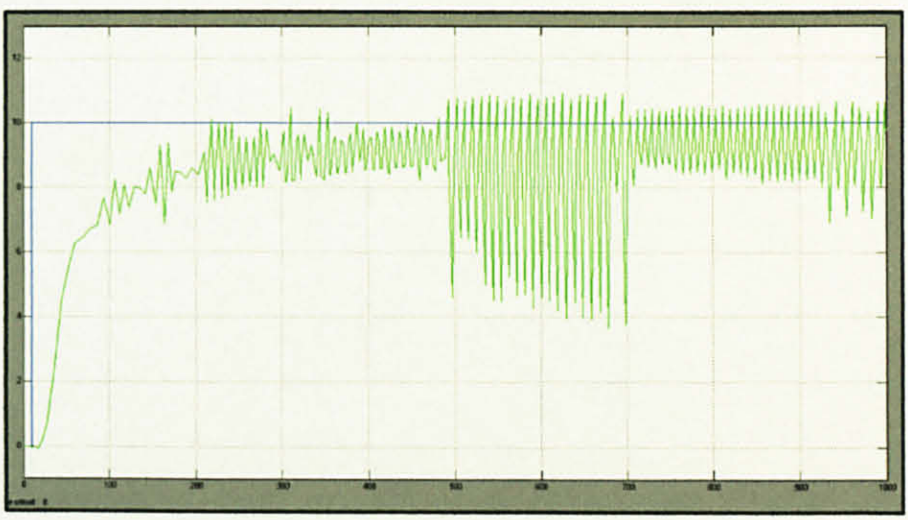

Figure 14: K=0.2, β=0, α=0.01

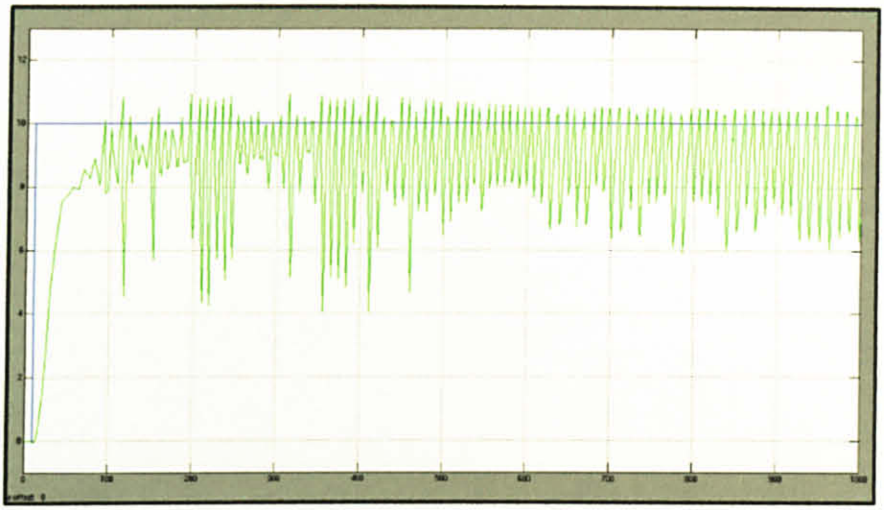

Figure 15: K=0.2, β=0, α=0.1

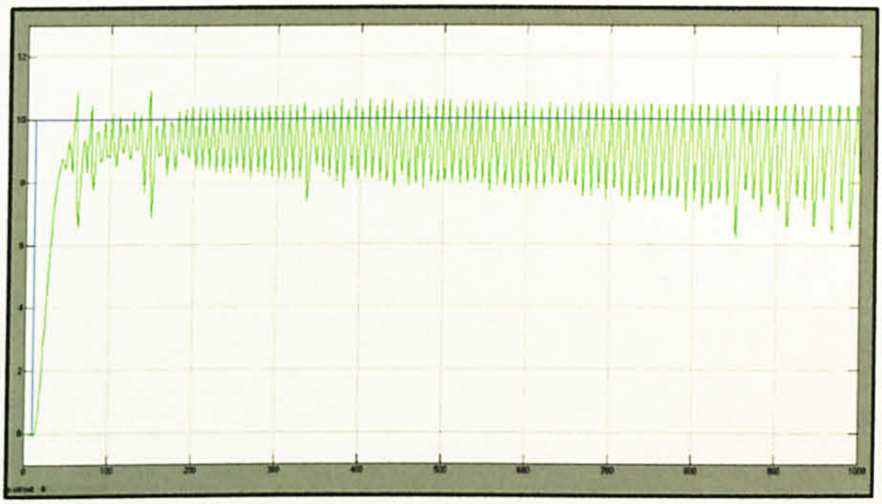

Figure 16: K=0.2, β=0, α=1

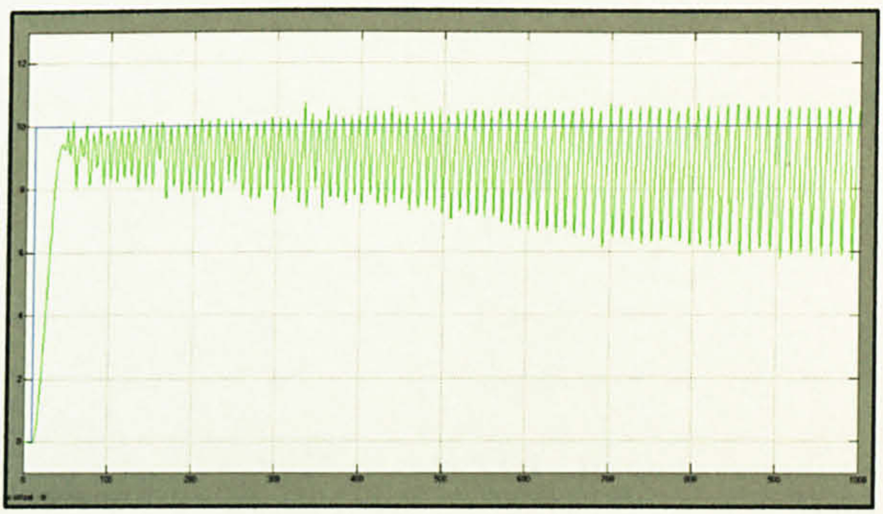

Figure 17: K=0.2, β=0, α=10

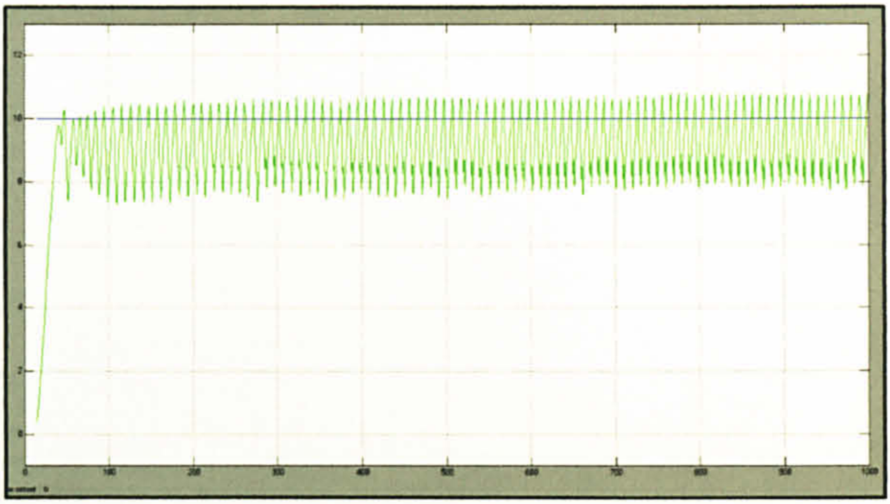

Figure 18: K=0.2, β=0, α=100

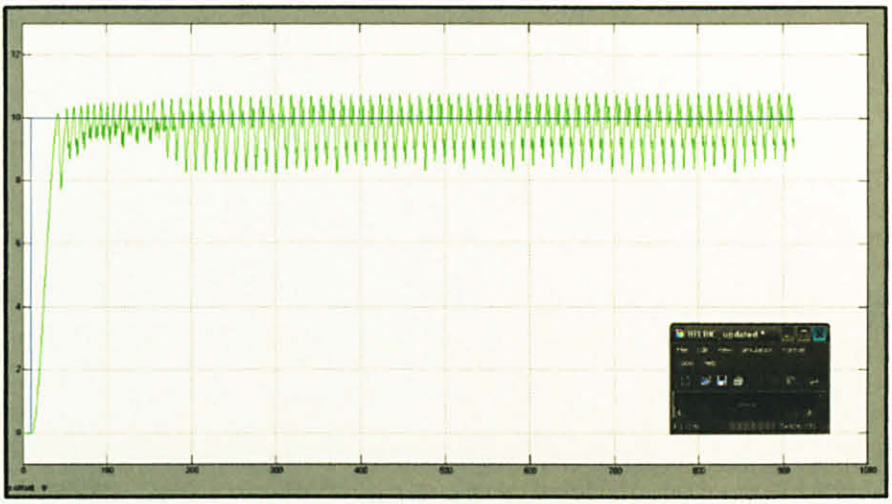

Figure 19: K=0.2, β=0, α=1000

From Figures 12 – 19, when the value of α increased, the steady state error of the process response decreases. The capability of the amygdala to 'learn' and response to the set point value is higher.

b. Effect of Learning Rate of Orbitofrontal Cortex (β)

Figures 20 – 27 show the effect of learning rate of orbitofrontal cortex for different values of β. Blue graph indicates set point and green graph indicates plant model response.

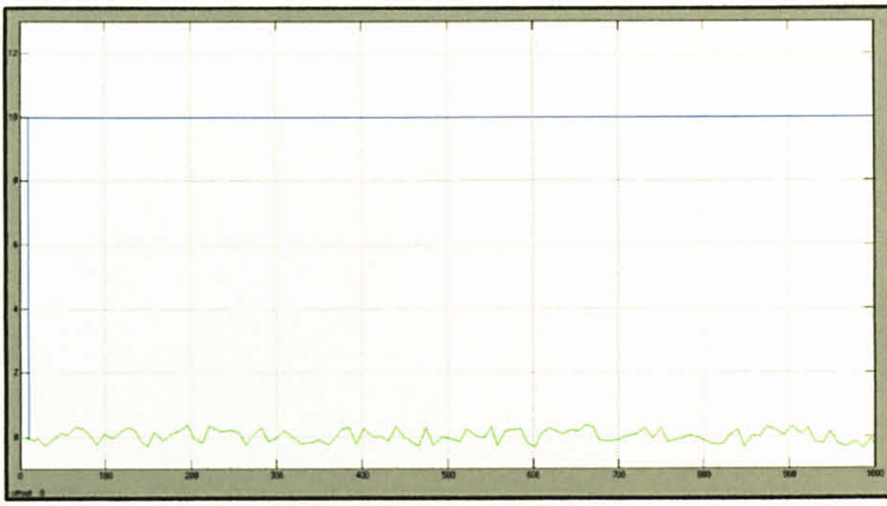

Figure 20: K=0.2, α=0, β=0

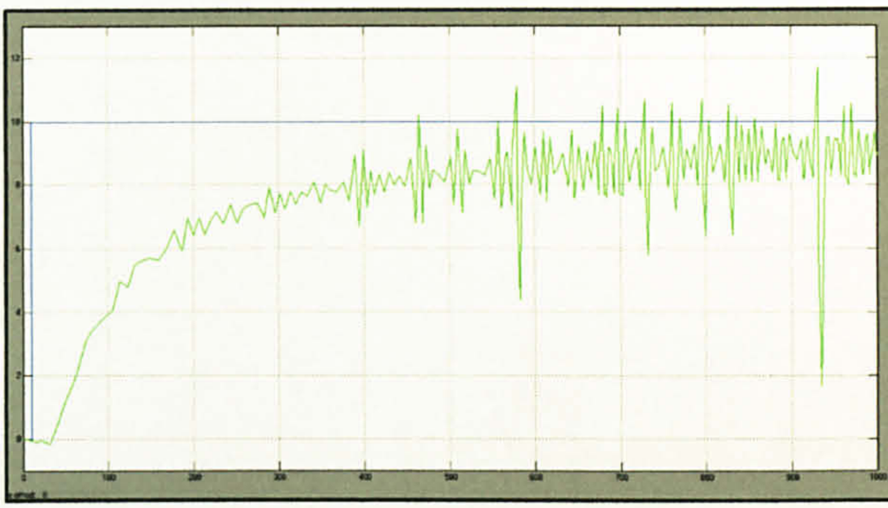

Figure 21: K=0.2, α=0, β=0.001

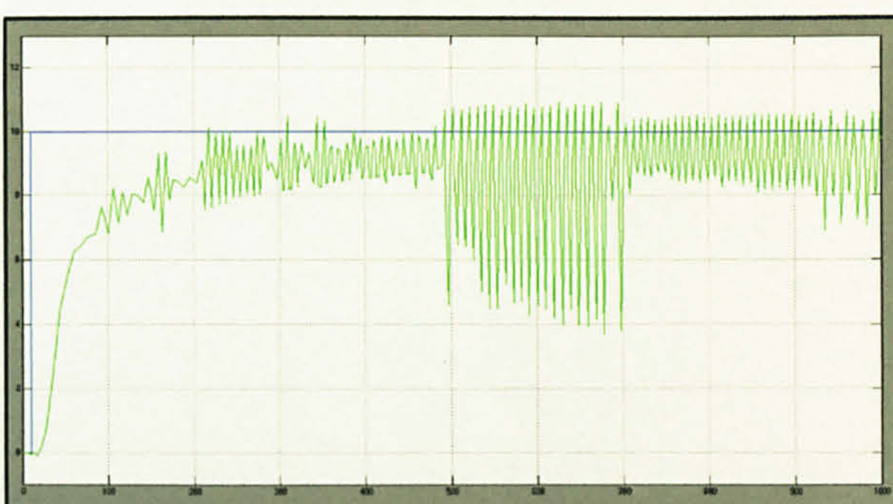

Figure 22: K=0.2, α=0, β=0.01

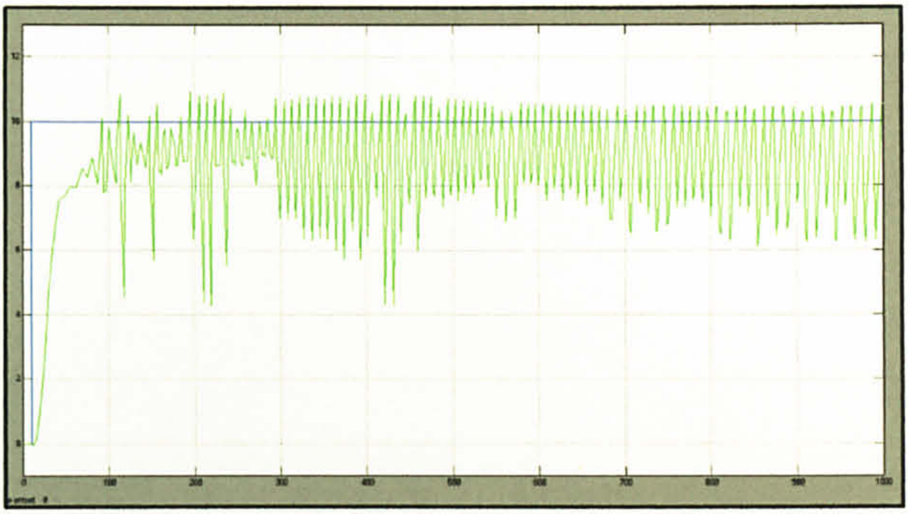

Figure 23: K=0.2, α=0, β=0.1

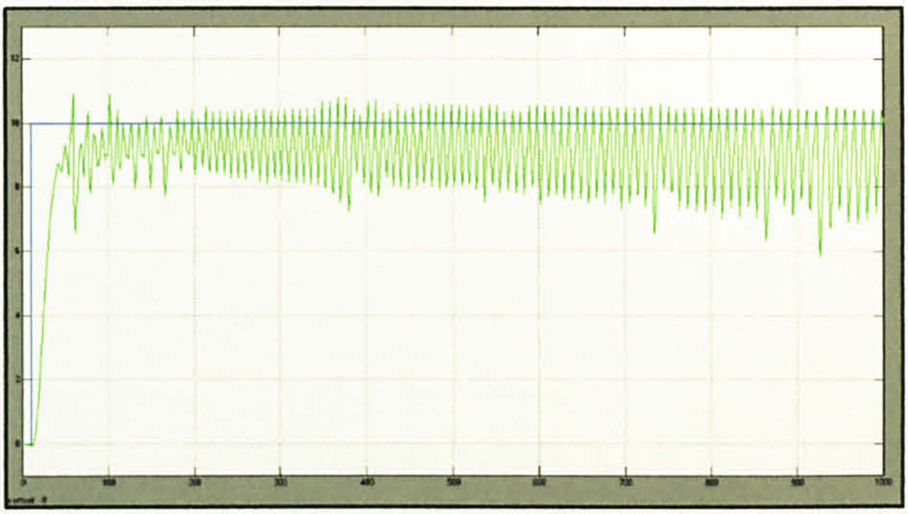

Figure 24: K=0.2, α=0, β=1

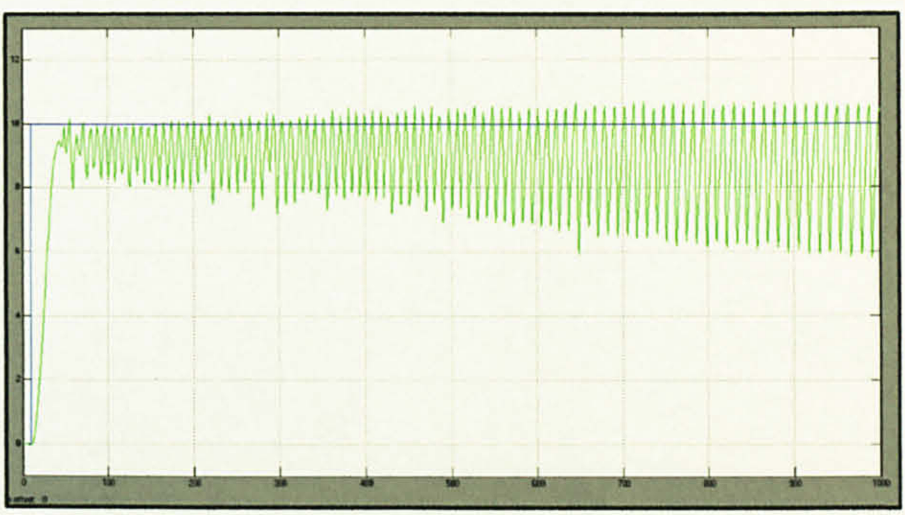

Figure 25: K=0.2, α=0, β=10

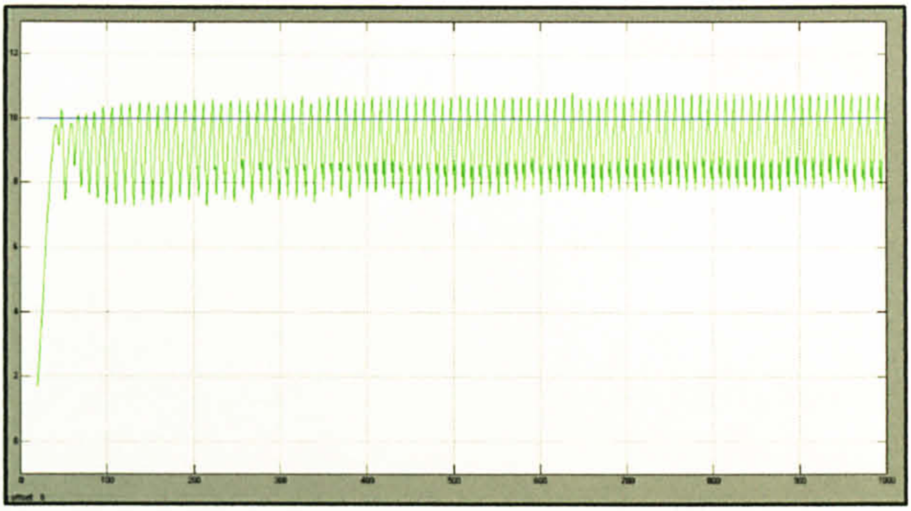

Figure 26: K=0.2, α=0, β=100

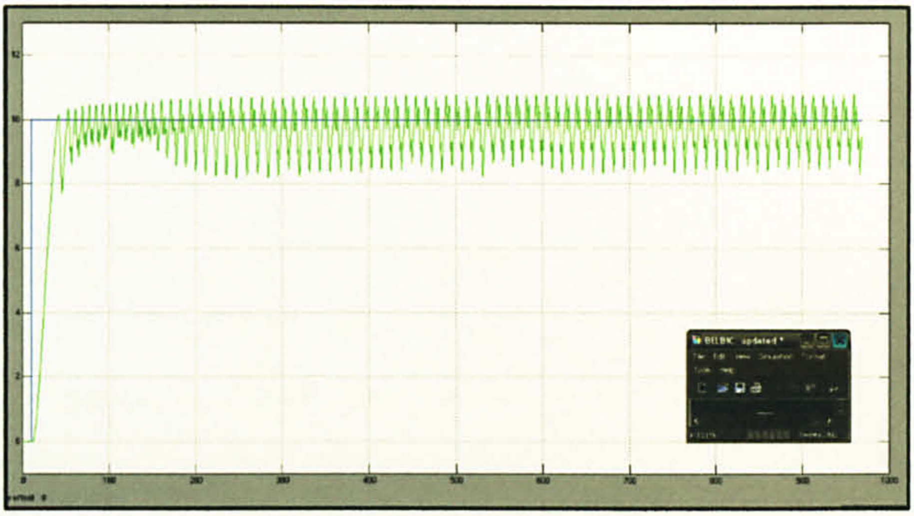

Figure 27: K=0.2, α=0, β=1000

From Figures 20 – 27, when the value of β increased, the steady state error of the process response decreases. The capability of the orbitofrontal cortex to 'learn' and response to the set point value is higher.

c. Effect of Reward Signal (rew)

Figures 28 – 32 show the effect of reward signal for different values of K. The reward signal function is rew=Ke+∫Kedt. α and β is randomly chosen to be 1000. Blue graph indicates set point and green graph indicates plant model response.

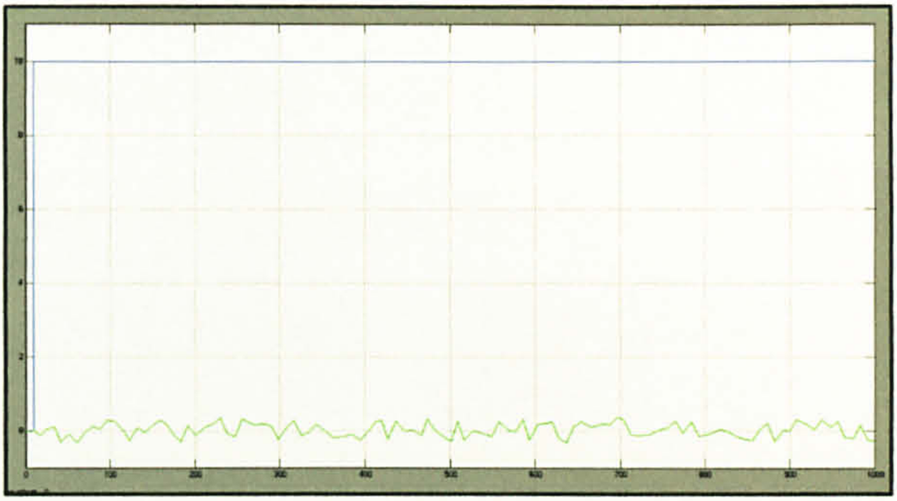

Figure 28: α=1000, β=1000, K=0

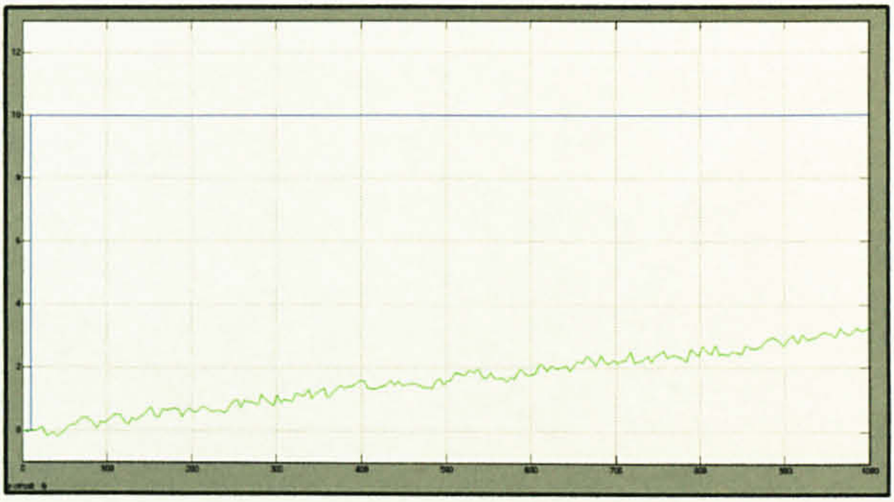

Figure 29: α=1000, β=1000, K=0.001

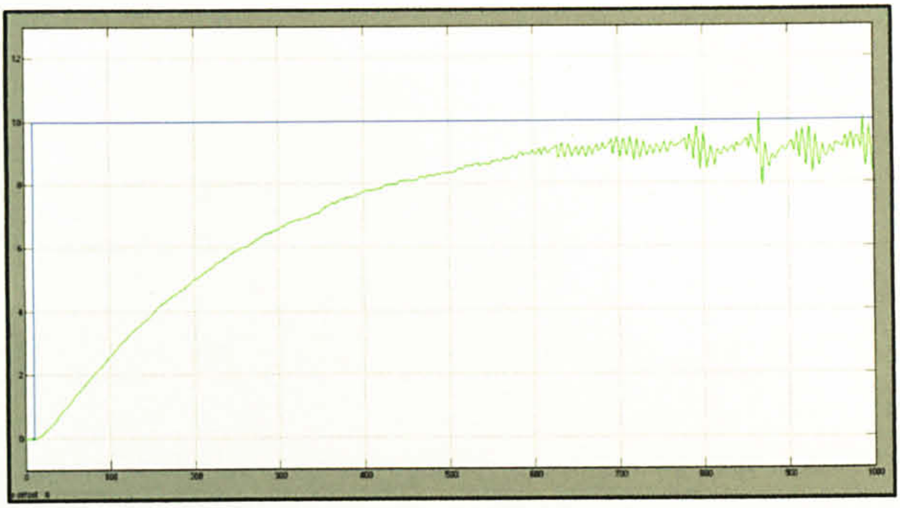

Figure 30: α=1000, β=1000, K=0.01

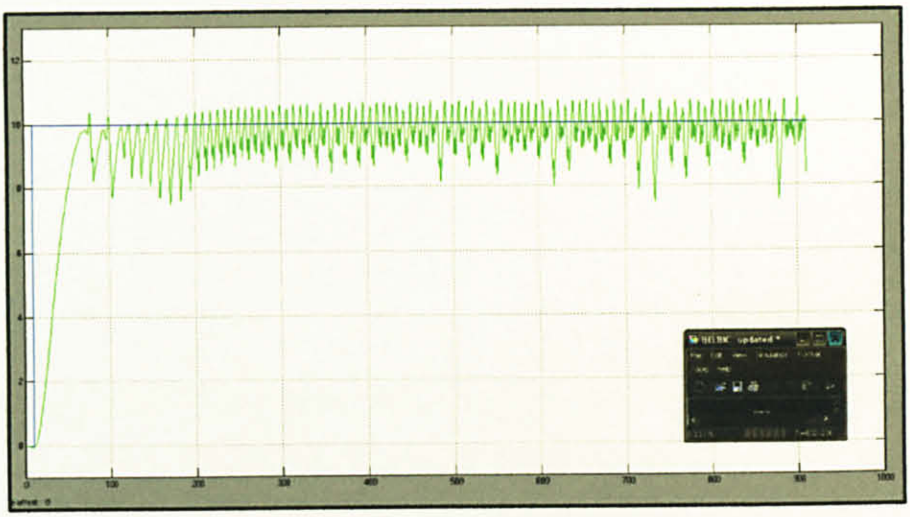

Figure 31: α=1000, β=1000, K=0.1

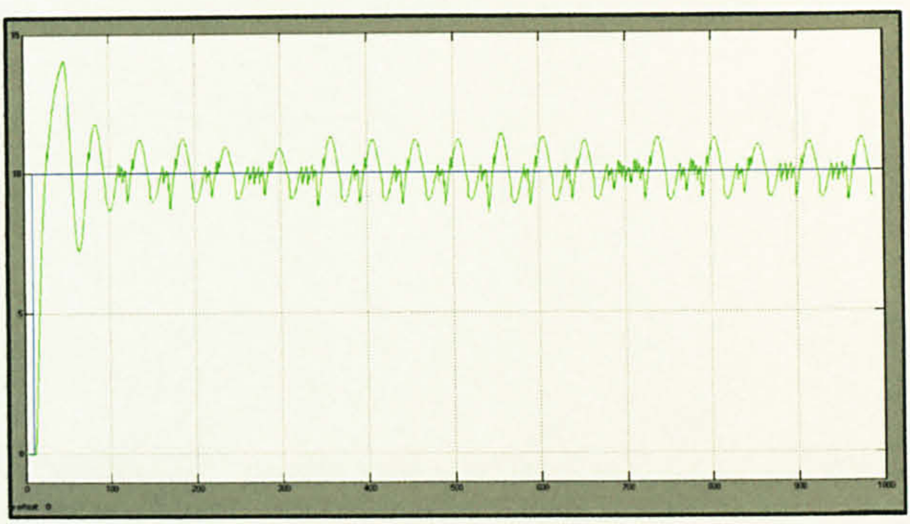

Figure 32: α=1000, β=1000, K=1

Reward signal is the most important tuning parameters of BELBIC and it is freely selected by the designer. From Figures 28 – 32, when the value of K is increased, the rise time and steady state error of the process response decrease. However, if the K value is further increased, the process response will have an overshoot.

After fine-tuning *α*, *β* and *rew*, the best response for the controller is shown on Figure 33.

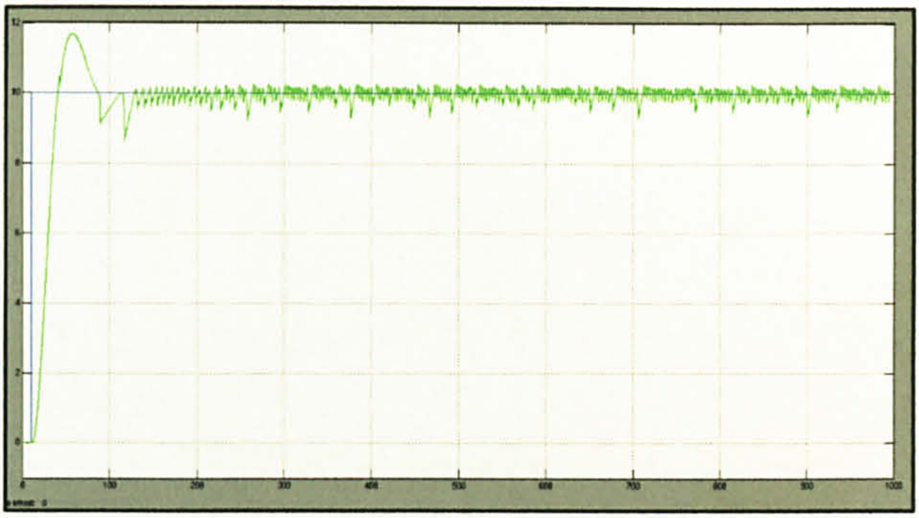

Figure 33: α=1e5, β=1e5, K=0.2

The best response of the controller for the said reward signal as shown in Figure 33 needs a very high value of *α* and *β* which increases the processing time of the controller resulting to low controller performance in terms of controller processing time. The reward signal is modified to be *rew* = K(e + kd e du/dt + ki ∫e dt + ku ∫u dt) and the plant model responses are analyzed in the next section.

d. Effect of the Modified Reward Signal (rew)

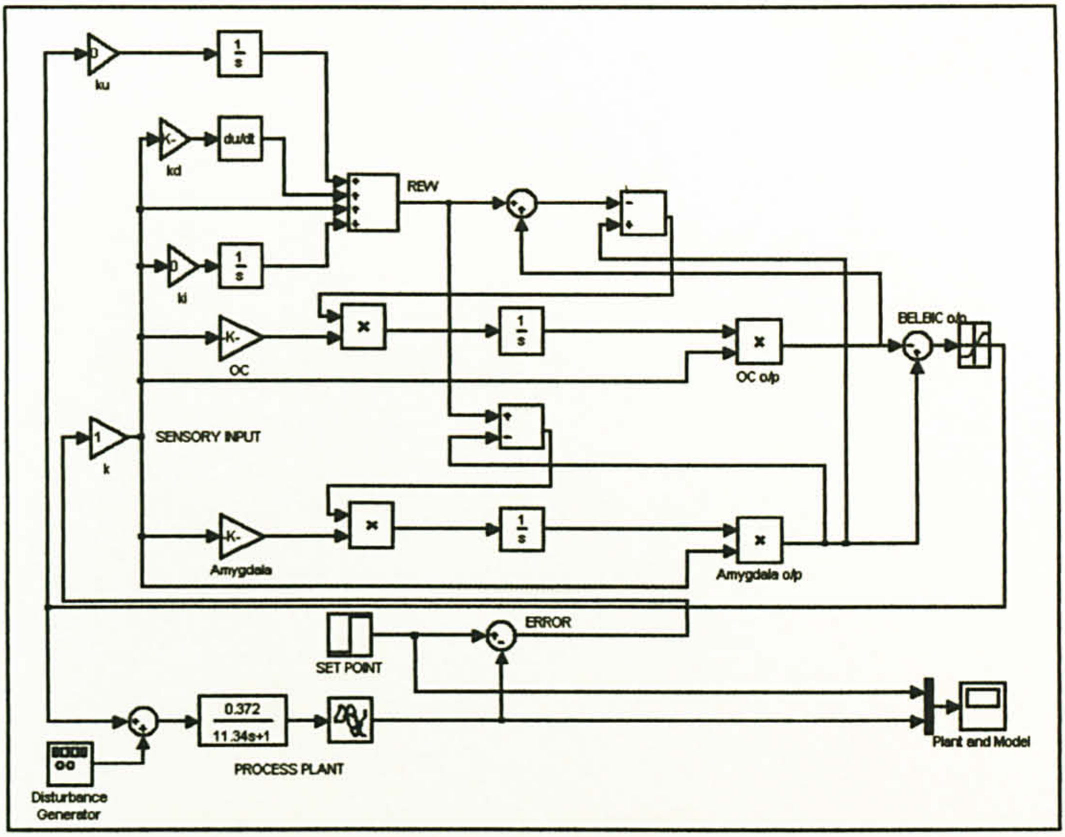

Figure 34: BELBIC schematic

Figure 34 shows BELBIC schematic for modified reward signal, *rew* = K(e + kd e du/dt + ki ∫e dt + ku ∫u dt).

The tuning parameters for the modified *rew* are K, kd, ki and ku. K is the gain of the controller; kd is the derivative constant of the error; ki is the integral constant of the error and ku is the integral constant of the output of the controller. The effect of every parameter in the *rew* is presented by Figures 35 – 41. After fine-tuning *α, β* and *rew*, the best response for the controller with the modified *rew* is shown on Figure 42.

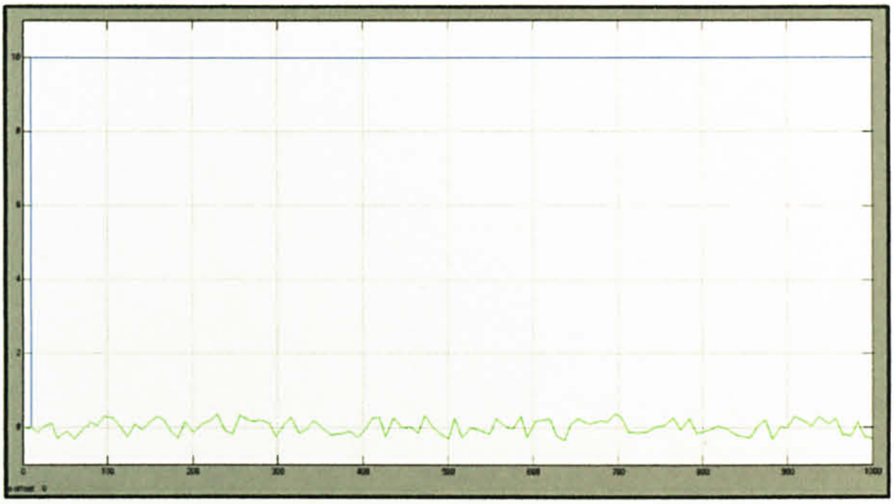

Figure 35: K=0, ki=1, ku=1, kd=1

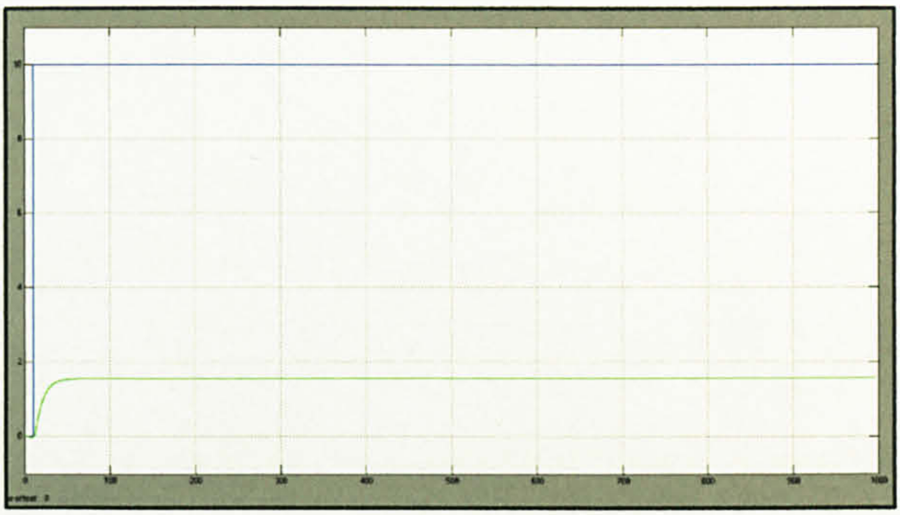

Figure 36: K=1, ki=0, ku=0, kd=0

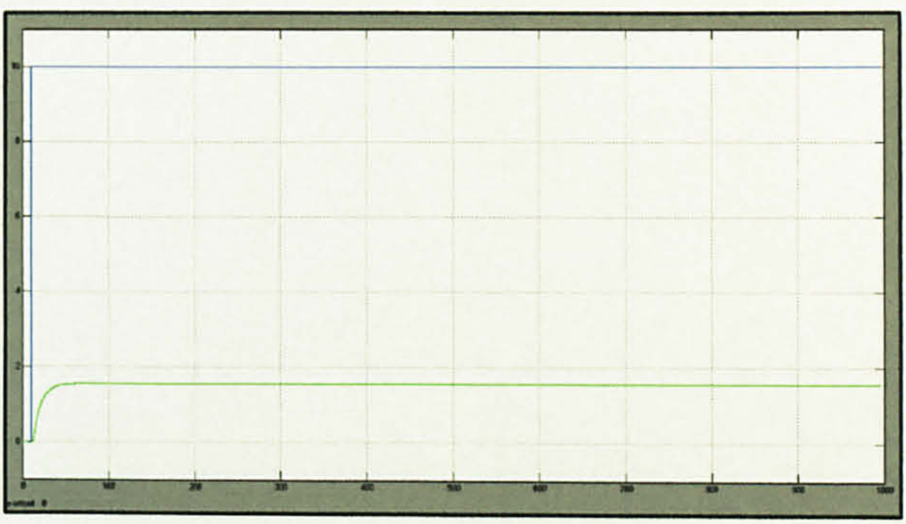

Figure 37: K=1, ki=0, ku=0, kd=1

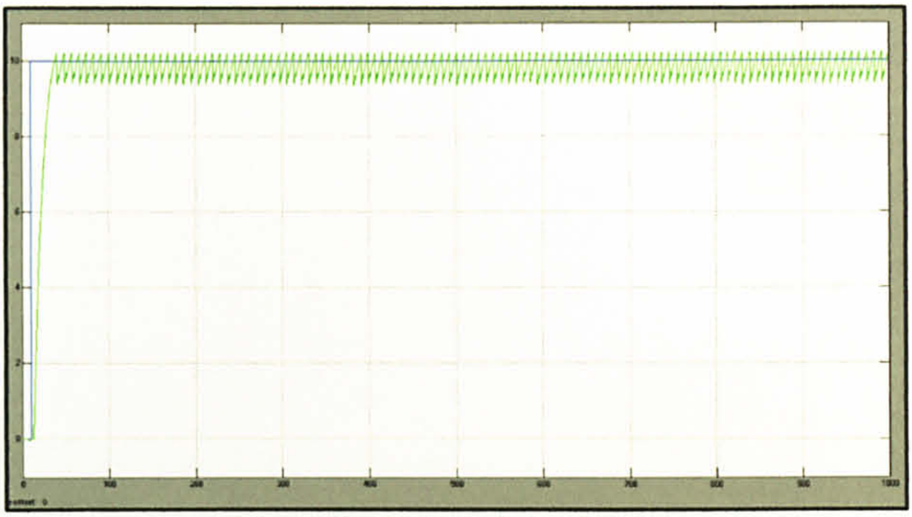

Figure 38: K=1, ki=1, ku=0, kd=0

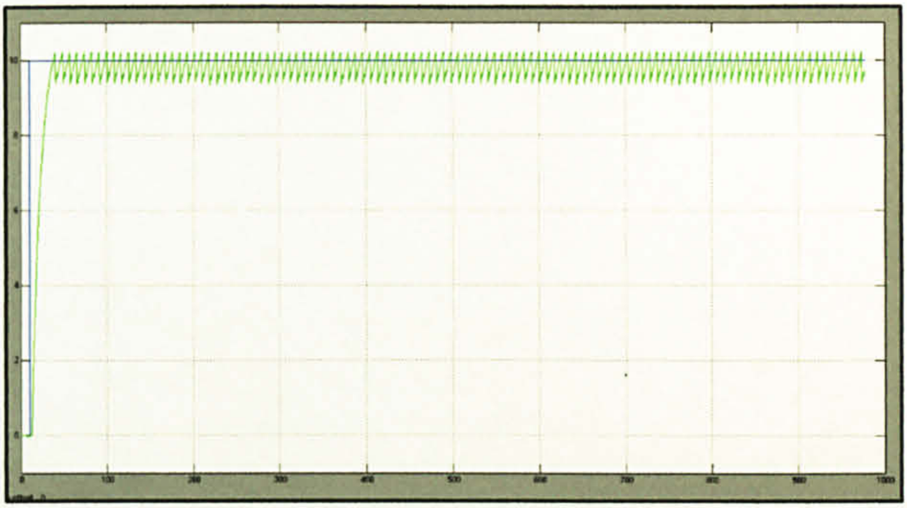

Figure 39: K=1, ki=0, ku=1, kd=0

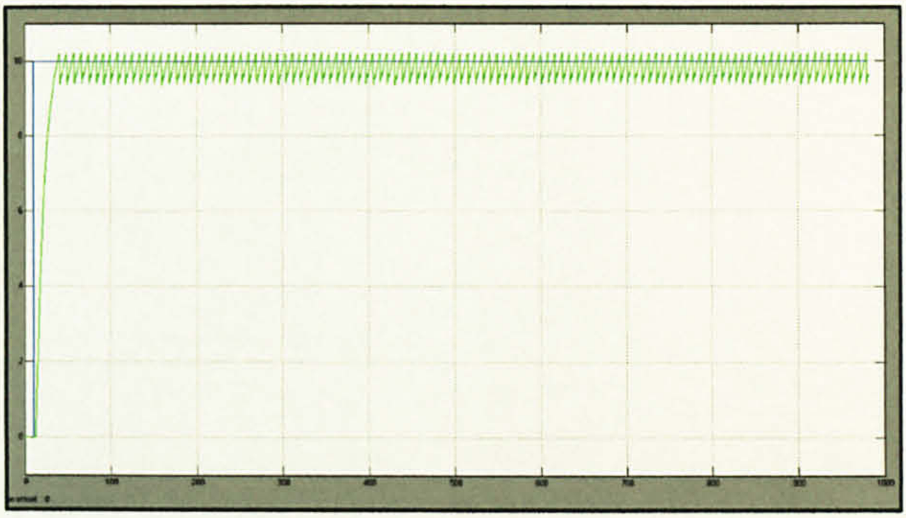

Figure 40: K=1, ki=1, ku=1, kd=0

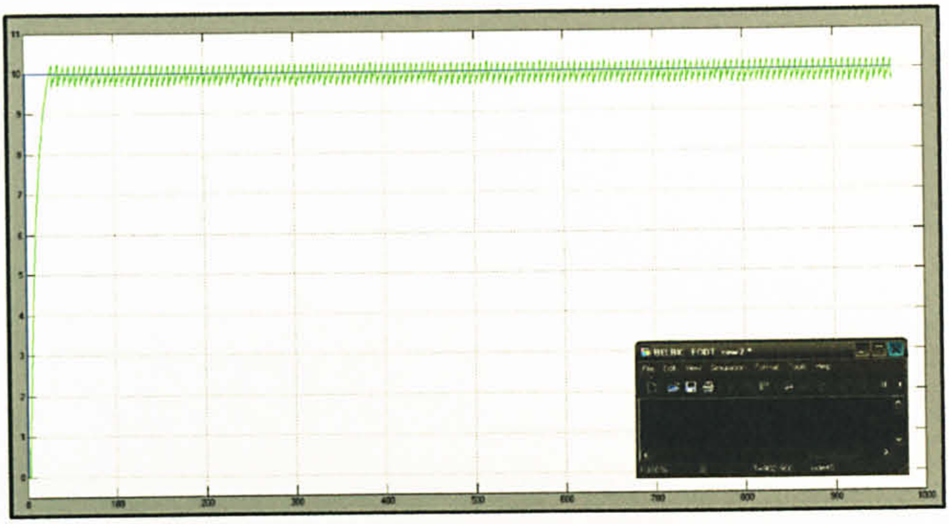

Figure 41: K=1, ki=1, ku=1, kd=1

K is a compulsory parameter in BELBIC. Figure 35 shows that the absence of K causes the controller to be unresponsive to the process variable and disturbance regardless the values of ki, ku and kd.

ki and ku play the same role in BELBIC; to bring the process variable to the set point. Integral action eliminates steady-state error of the controller response. Figure 36 and Figure 37 show the importance of ki and ku in eliminating steady-state error. Figure 38 and Figure 39 show that both ki and ku work the same way; to eliminate steady-state error. Applying ki or ku alone needs the and β values to be high which resulting to a longer processing time. Incorporating together ki and ku will resort the controller response to be more robust and need only low α and β values.

Figures 38 – 40 show that kd does not affect the steady-state error of the controller response.

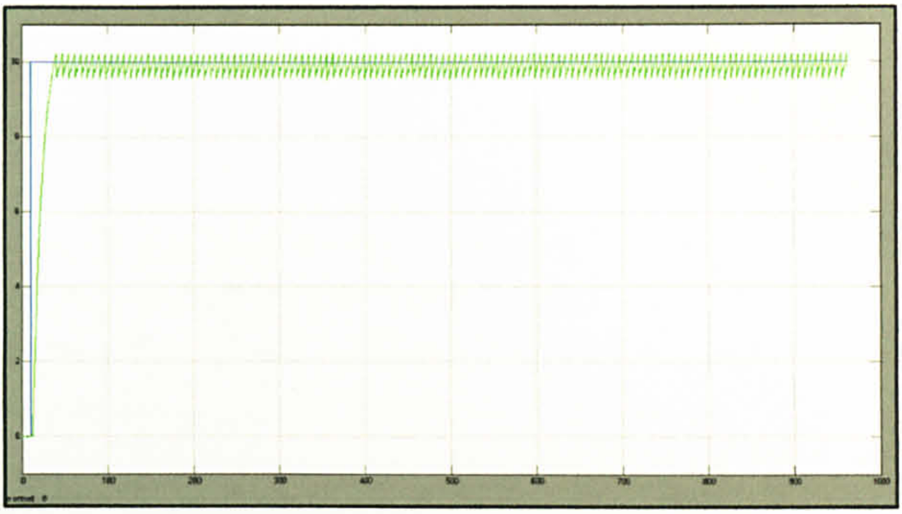

Figure 42: BELBIC response after fine-tuned

4.2.3 BELBIC Performance

Figure 11 shows the process response without controller action. There is large steady-state error and the process variable never reaches the set point. With BELBIC controller; as shown in Figure 42, the steady-state error is within ±5% with no overshoot. BELBIC compensates for disturbance very well.

Table 4: BELBIC performance after fine tuning

Settling Time, Ts (s)	23.9
Rise Time, Tr (s)	16.7
% Overshoot, %OS	-

4.3 PID Controller

4.3.1 PID Controller Tuning Parameters

Using Cohen-Coon Tuning Correlation and Ziegler Nichols Close Loop tuning method, the parameters for the PID controller are obtained (See Table 5 and Table 6). The Cohen-Coon Tuning Correlation and Ziegler Nichols close loop methods tuning parameters formulas are given in Appendix B.

Table 5: PID tuning parameters using Cohen-Coon tuning correlation

Controller mode	K_C	T_I	T_D
PID	18.116	0.1891 min	0.8168 min

Table 6: PID tuning parameters using Ziegler-Nichols closed loop tuning method

Controller mode	K_C	T_I	T_D
PID	13.2	4.5 s	1.1 s

Table 7: PID tuning parameters after fine tune

Controller mode	K_C	T_I	T_D
PID	20.0	0.15 s	1.0 s

4.3.2 PID Controller Responses

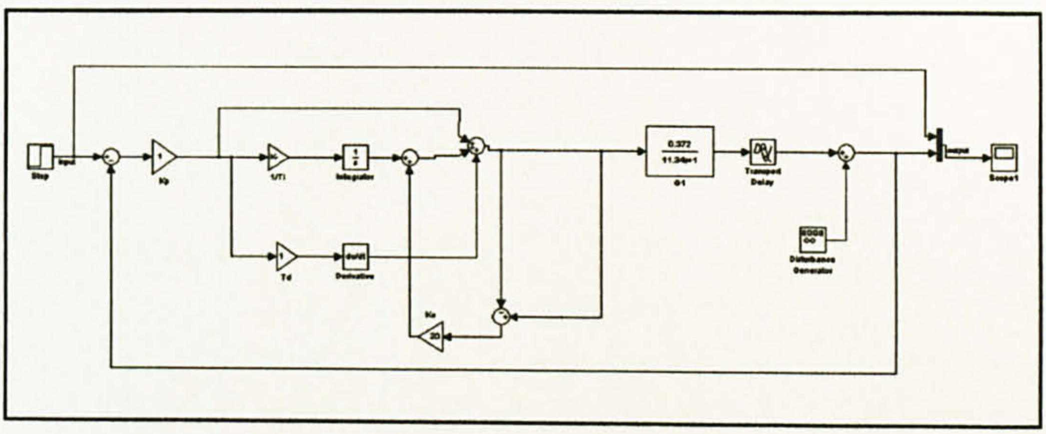

Figure 43: PID controller schematic

PID controller schematic in SIMULINK is shown in Figure 43. A step input of value 10 is used as the set point. A random disturbance with amplitude of 1 is used as the disturbance signal. Two different methods; Cohen-Coon tuning correlations and Ziegler-Nichols closed loop tuning method are used to tune the PID controller. Ciancone method is also an alternative in order to tune the controller; however, the error is expected to be larger as the tuning constants are calculated via graph.

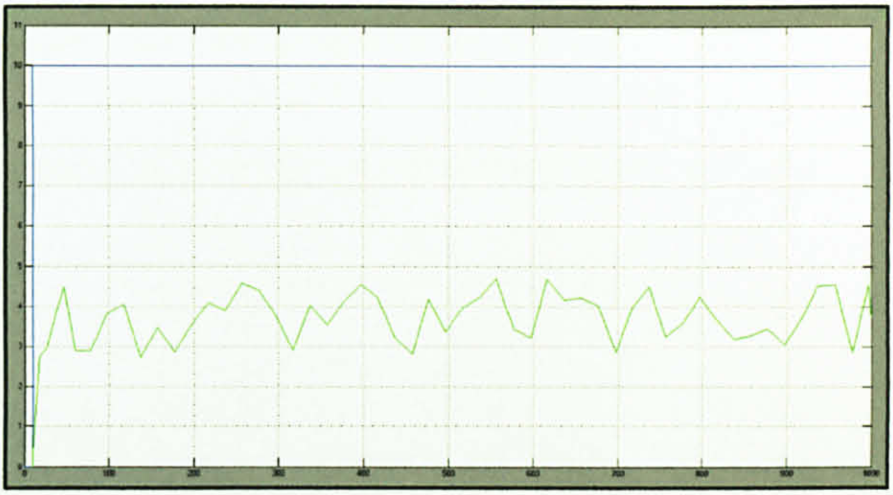

Figure 44: Process response without controller

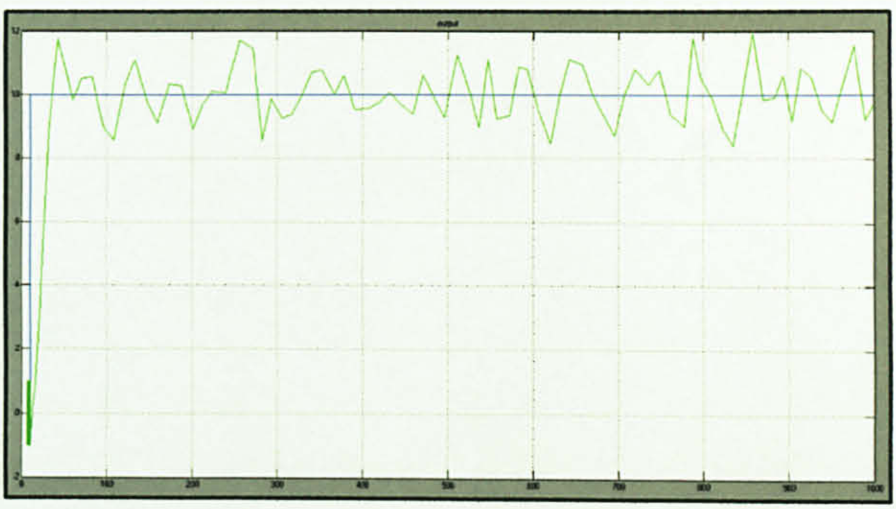

Figure 45: Cohen-Coon response

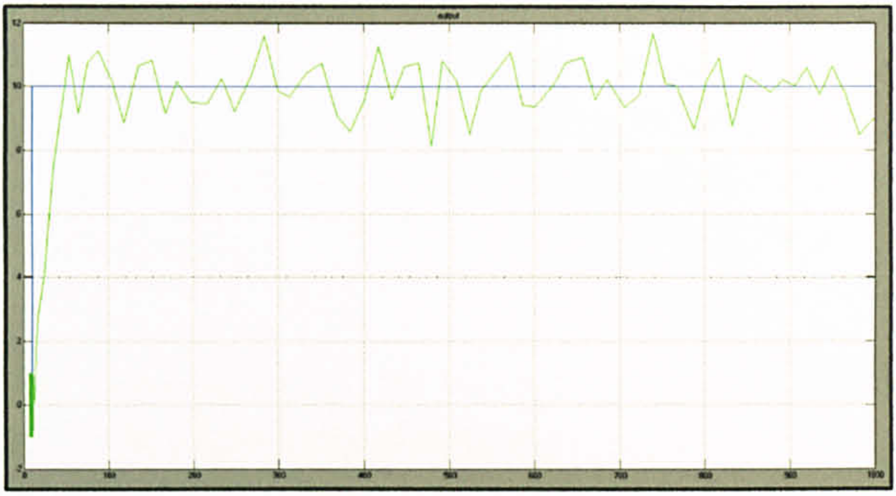

Figure 46: ZN closed-loop response

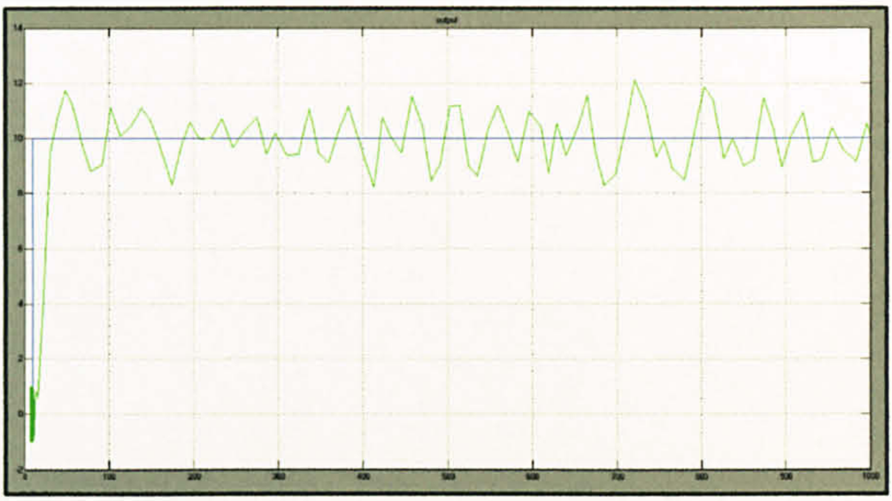

Figure 47: PID controller response after fine tuning

4.3.3 PID Controller Performance

Figure 44 shows the process response without controller action. There is large steady-state error and the process variable never reaches the set point. Due to the random disturbance, the steady-state response fluctuates between ±20% from the set point value. From Figure 45 and Figure 46, the performance of PID controller using different tuning methods is simplified in Table 8.

Table 8: PID controller performance

	Cohen-Coon	Z-N Closed Loop
Settling Time, Ts (s)	-	-
Rise Time, Tr (s)	20	30
% Overshoot, %OS	11.6%	9.5%

After fine tuning, the PID controller response is shown in Figure 47. The performance of the PID controller is simplified in Table 9 below:

Table 9: PID controller performance after fine tuning

Settling Time, Ts (s)	-
Rise Time, Tr (s)	17
% Overshoot, %OS	17.5%

4.4 BELBIC and PID Controller Performance Comparison

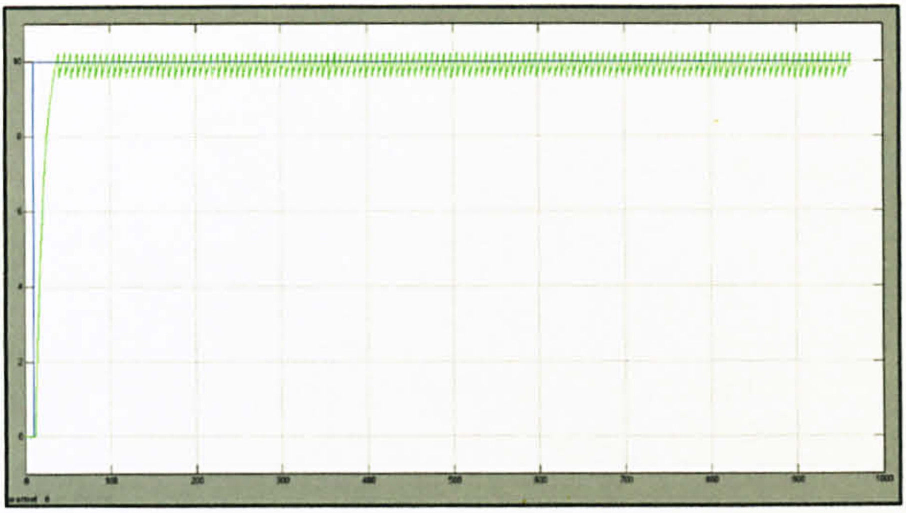

Figure 48: BELBIC performance

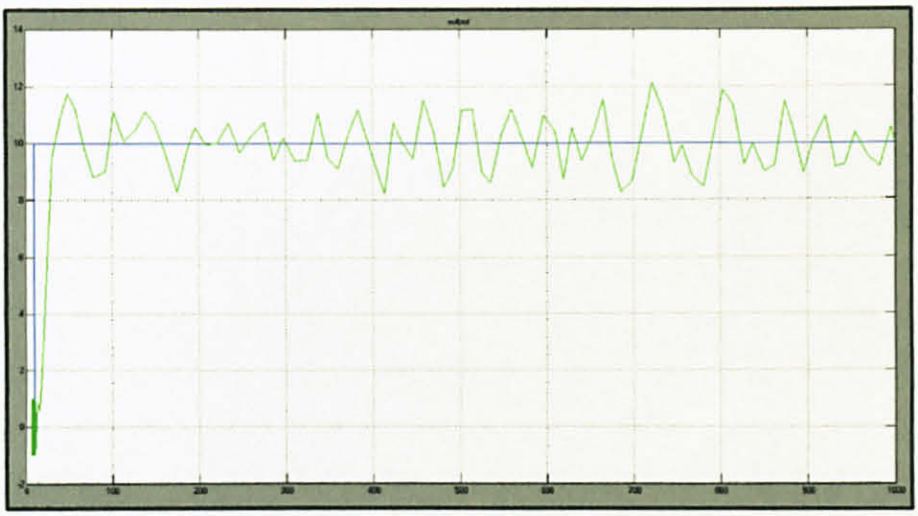

Figure 49: PID controller performance

Figure 48 and Figure 49 show the simulation results of BELBIC plant model and PID controller plant model. Table 10 shows the performance of both controllers in terms of settling time (Ts), rise time (Tr) and overshoot percentage (%OS). Performance of BELBIC is better than that of PID controller with short Ts, shorter Tr and lesser overshoot.

Table 10: BELBIC and PID controller performance comparison

	BELBIC	PID Controller
Settling Time, Ts (s)	23.9	-
Rise Time, Tr (s)	16.7	17
% Overshoot, %OS	-	17.5%

4.5 Discussions

The integral application is included in BELBIC in building algorithms for amygdala, orbitofrontal cortex and reward signal. Integration is applied to eliminate steady-state offset, which it does satisfactorily as long as it has the ability to adjust the final element. When the final element reaches a limit, a difficulty is encountered that is related to the controller algorithm and must be addressed with a modification to the algorithm. When the final element cannot be adjusted, the error remains nonzero for a long period of time, and the amygdala, orbitofrontal cortex and reward signal algorithm continues to calculate values for the controller output. Since the error cannot be reduced to zero, the amygdala, orbitofrontal cortex and reward signal algorithm integrate the error, which is essentially constant, over a long period of time; the result is a controller output value with a very large magnitude. Since the final element can change only within a restricted range, these large magnitudes for the controller output are meaningless, because they do not affect the process, and should be prevented. Due to this, windup must be taken care of when designing BELBIC as it uses much integration in the algorithm.

Applying derivative to the reward signal will make the controller responses to the rate of change of the error. Derivative should give a shorter Tr. However, applying derivative in the reward signal causes the processing time of BELBIC to be long which would result the performance of the controller to be degraded. This is observed at the beginning of the simulation; when the rate of change of the error is much higher (due to the dead time of the process and small plant gain), the processing time of the controller is very slow.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Brain emotional learning based intelligent controller or BELBIC is one of artificial intelligent controllers. BELBIC algorithm is much simpler as compared to other artificial intelligent controller algorithm. Learning rate of amygdala and learning rate of orbitofrontal cortex are two parameters in BELBIC that associate the error with the control. Reward signal is the key in gearing BELBIC to give a better control on the process variable.

BELBIC algorithm and PID algorithm are applied in this project. Feedback control and anti-reset windup are also used to build the controllers. BELBIC is tuned using trial and error method to achieve the best controller performance. For PID controller, Cohen-Coon Correlation, Ziegler-Nichols Closed Loop tuning methods and fine-tuning method are used to tune the controller to get the best controller performance.

BELBIC has shown a better performance with a shorter settling time and shorter rise time. BELBIC also does well in regulating disturbance. In BELBIC, integral windup must be taken care of because it involves much integration in building the algorithm. This project has shown that BELBIC gives very good performance for system with dead time and system with disturbance. From the results presented, it can be concluded that BELBIC is applicable for temperature control application.

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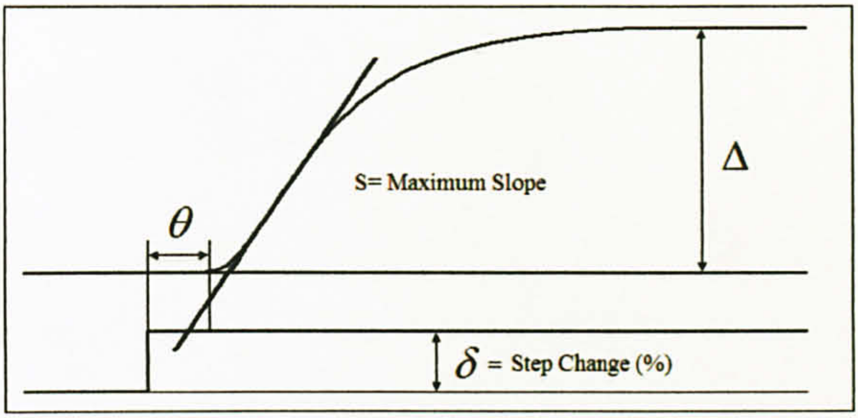
APPENDICES

APPENDIX A

Method I and Method II

Method I



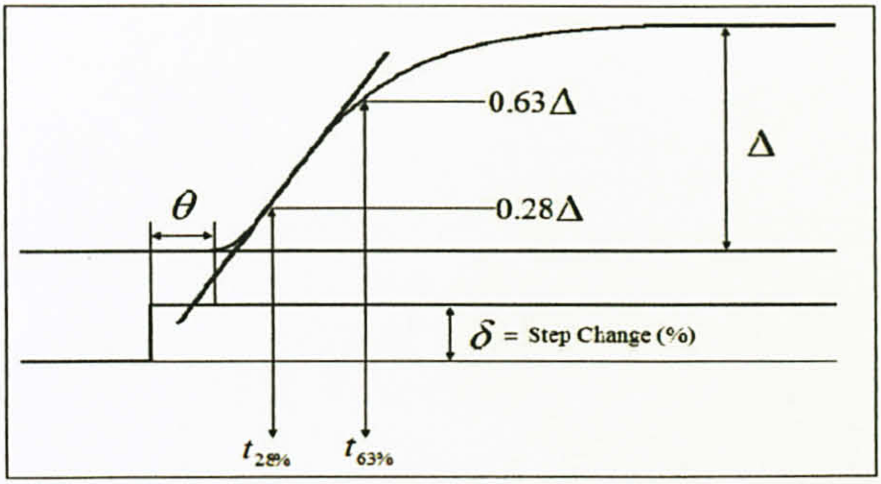
The process parameters are determined as:

$$Kp = \frac{\tau}{\delta}$$

$$\tau = \frac{\Delta}{s}$$

θ= Interception of maximum slope with initial value (as shown in the above PRC graph).

Method II



The process parameters are determined as:

$$Kp = \frac{\tau}{\delta}$$

$$\tau = 1.5\ (t_{63\%} - t_{28\%})$$

$$\theta = t_{63\%} - \tau$$

APPENDIX B

PID Controller Tuning Parameters Formulas

Ziegler-Nichols Closed Loop

$$K_C = \frac{K_U}{1.7}$$

$$T_I = \frac{P_U}{2.0}$$

$$T_D = \frac{P_U}{8}$$

Cohen-Coon Tuning Correlations

$$K_C = \frac{1}{K_P}\frac{\tau}{\theta}\left[\frac{3\theta + 16\tau}{12\tau}\right]$$

$$T_I = \theta\frac{\left[32 + 6\frac{\theta}{\tau}\right]}{13 + 8\frac{\theta}{\tau}}$$

$$T_D = \frac{4\theta}{11 + 2\frac{\theta}{\tau}}$$